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The impact of social media conversations on consumer brand choices

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Abstract This paper estimates the impact of social media conversations on consumer valuation of brand characteristics and demand for carbonated soft drinks (CSDs). We formulate a random coefficient, discrete choice model of consumer demand that includes social media conversations, and estimate it matching Nielsen sales data on carbonated soft drinks to social media conversations on Facebook, Twitter, and YouTube. Empirical results indicate that consumers' conversations about brands and nutritional aspects of CSDs have a significant impact on their valuation of brand characteristics and ultimately on their choices of CSDs. These findings have important implications not only for firms using social media as a strategic tool for effective brand promotion and product design but also for public health policies aimed at reducing the consumption of sugary beverages and high-calorie foods.

Keywords Social media · Word-of-mouth · Demand · Consumer behavior · Internet · Carbonated soft drinks

JEL Classification D12 · M37 · L66

1 Introduction

Word-of-mouth (WOM) via social media has become a key driver of brand recommendation among consumers, prompting an increasing number of companies to promote their products and services through social media in order to stimulate consumer

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conversations, increase consumer loyalty, and acquire new customers (Hoffman and Fodor 2010; Financial Times Special 2012). [1] By facilitating WOM, social media have significantly altered the balance of marketing communication from unidirectional (firms to consumers as in traditional advertising) to bidirectional (among consumers) in many consumer markets.

Social media consumer-to-consumer exchange is a relatively new type of online WOM. Most previous studies have focused on the effects of Internet penetration and the interaction between online and offline company advertising (e.g., Trusov et al. 2009; Smith and Telang 2010; Goldfarb and Tucker 2011; Orlov 2011; Liebowitz and Zentner 2012). Regarding WOM, studies have focused on the effects of online WOM on product sales. For instance, Onishi and Manchanda (2012) found that prelaunch TV product advertising spurs blogging and acts synergistically in product sales. Bruce, Foutz, and Kolsarici (2012) showed that advertising and WOM on the theater-then-video sequential distribution of motion pictures exert dynamic and diverse effects on sales of new products. Rui, Liu, and Whinston (2013) found that chatter on Twitter affects movie sales, but the magnitude and direction of the effect depend on the source and nature of WOM communication. In spite of the growing importance of social media WOM, there is a lack of empirical evidence on its effects on consumer preferences and brand choices.

This article investigates the impact of social media conversations on US consumers' preferences in the carbonated-soft-drink (CSD) market. This market provides a good case study for examining the effects of social media conversations on consumer brand choices for several reasons. First, the CSD market is characterized by a strong presence of company social media websites and consumer conversations, particularly those aimed at the industry leader, the Coca-Cola Company—the most popular among Facebook users and other social media communities in the food and beverage sector (Forbes 2013). Second, the products are differentiated at the brand level so that the effects of brand and nutrition conversations on sales of particular brands can be discerned. Third, there is a public health interest in potential policy instruments, such as advertising or social media, that affect the consumption of sugary CSDs due to the ongoing obesity epidemic in which CSDs have been identified as an important contributor. [2] Understanding how social media WOM affects consumer valuation of characteristics and choices of CSD products can be helpful in understanding and informing firm strategies aimed at effectively designing and promoting products.

To quantify the impacts of social media on consumer demand, we estimate a random coefficient logit model of demand. Product characteristics include goodwill measures of social media WOM as well as nutritional characteristics of CSDs and their interactions. The empirical results suggest that WOM about brands and nutritional aspects of CSDs have a significant impact on consumers' choices and, hence, demand for specific

[1] As used in this article, social media include social networks (e.g., Facebook), video-sharing sites (e.g., YouTube), microblogging (e.g., Twitter), etc. This is of course a simplification of the social media universe, which includes other means by which people create, share, and/or exchange information and ideas in virtual communities and networks, including consumer product reviews on Yelp, Google, Amazon, and many other sites.

[2] Although this point is often raised by public health advocates and public officials, companies continue to lobby against policies to restrict CSD consumption, such as restricting advertising and container sizes and imposing taxes (Liu et al. 2014).

types of CSDs. Further, based on the demand parameter estimates, we simulate the market shares for all brands under alternative scenarios. We find that Coke and Pepsi would experience the largest decrease in market shares without brand social media conversations and that sugary CSDs would suffer larger losses with a higher level of conversations about sugar. These findings have important implications not only for firm strategy but also for potential public health policies aimed at reducing the consumption of sugary beverages and high-calorie foods.

2 Data

Two Nielsen Company datasets are used at the product brand level: CSD sales data and social media data. Monthly sales data on 18 CSD brands were collected over 12 designated market areas (DMAs) from April 2011 through October 2012.[3] These data include DMA-level data on dollars sales, volume sales, and prices for diet and regular CSDs for supermarkets with more than $2 million annual sales.

The social media data cover the time period April 2011 through October 2012, matching the sales data. The Nielsen Company monitored and collected social media content for beverage products from various publicly available online social media communities such as Facebook, YouTube, and Twitter. For example, there are conversations like "ordering diet Coke with chips because you're healthy and not going to get any fatter with your meal because it's diet Coke," or "Seem like Pepsi drinks is getting stronger every day." Specifically, Nielsen measures the number of messages/discussions mentioning specific CSD brands in a day. Every time a consumer talks about a CSD brand on social media, the company gains increased exposure for its brand. Such increased brand awareness strengthens the association of the brand in consumers' minds and affects product demand.

Upon request, Nielsen uses codes to measure the sentiment expressed regarding each product (positive, negative, or neutral) in each conversation or WOM during the sample period. For example, comments like "Pepsi and Coke taste the same to me" are considered to be neutral, while "I love the smell of Coke in the morning" is positive. We record the volume of positive and negative WOM and calculate a social media score[4] for each brand in each month as:

$$\text{Social Media Sentiment Score} = \frac{\text{Positive WOM}-\text{Negative WOM}}{\text{Positive WOM} + \text{Negative WOM}}$$

The social media score, reflecting the total sentiment for any given period, takes a value from −1 to +1 based on the number of negative and positive conversations, respectively.

In addition, we collected social media conversations and consumer sentiment about sugar and caffeine content of CSDs. As shown in Fig. 1, consumers' social media

[3] The DMAs are New York, Detroit, Atlanta, Chicago, Los Angeles, Boston, Hartford/New Haven, Syracuse, Dallas, Miami, San Francisco, and Seattle.

[4] Shweidel, Moe and Boudreaux (2011) construct the social media sentiment score from various social media services and find that the different types of social media services developed brand sentiments in different situations. However, in our data, the great majority of all conversations come from one site—Twitter. Therefore, we only use one online sentiment score.

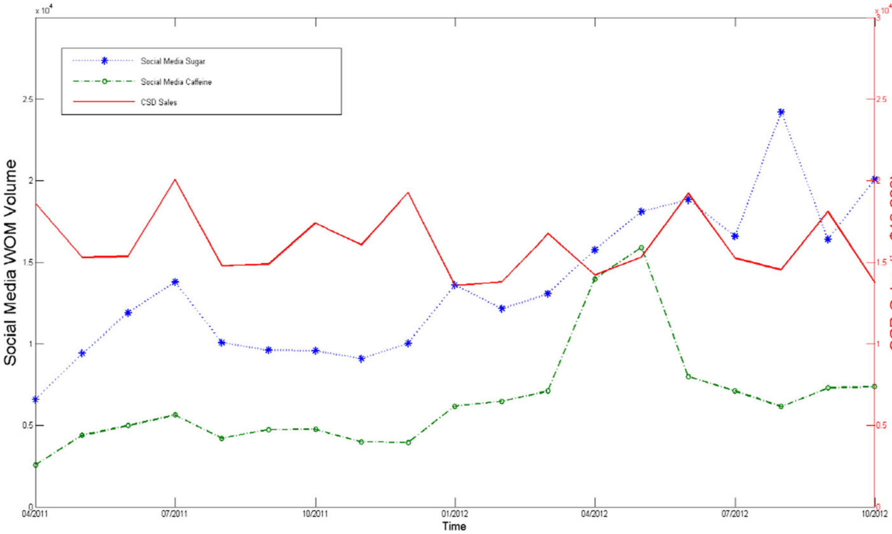

Fig. 1 Social media conversations on sugar and caffeine and CSD sales

conversations regarding sugar skyrocketed in the sample period, rising from 6,557 in April 2011 to 20,055 in October 2012. This pattern reflects the public's increasing awareness of sugar-related health issues. On average, there were 13,611 conversations on sugar and 6,554 conversations on caffeine recorded per month. The sentiment scores are −0.09 and −0.06 for sugar and caffeine content in CSDs, respectively, suggesting an overall negative attitude. More consumers looking for and sharing nutritional and health information through social media will help identify how social media affect consumers' preferences for nutritional content of a CSD brand. It also is interesting to notice that, in contrast to the rising nutrition-related conversations as well as the negative sentiments associated with them, total CSD sales of all brands in our sample experienced a slight downward trend during the same period, paralleling a broad decline in US consumption of CSDs in the same period (Zmuda 2012; Reuters 2012).

There are other factors, e.g., media coverage, that make the public become more aware of the potential health issues of CSDs. Therefore, we built a goodwill stock of the traditional media coverage of health news linked to CSD consumption and incorporate it into the model. LexisNexis Academic provides access to thousands of information sources covering news and legal, business, and other topics. We use the number of articles and transcripts from LexisNexis Academic as proxies to capture health information received by consumers.

Table 1 provides summary statistics of variables for all 18 brands used in the study. The sugar content of regular CSDs ranges from 3.25 g to 4.17 g per ounce, whereas that of all diet CSDs is zero. The sales-weighted average ranges from 2.46 to 2.97 cents per ounce. Following the conventional definitions of markets in previous discrete choice demand work (Chan 2006; Lopez and Fantuzzi 2012), we define a distinct market for each combination of DMA and time period. With consumers having the outside option of not buying, the market size used to compute market shares is the total volume consumption of CSDs, liquid tea, fruit juice, milk, and bottled water, calculated as per capita consumption × population. Market shares are calculated by total volume sold.

Table 1 Summary statistics: averages across cities and months

Brand	Sugar (g/oz)	Sodium (mg/oz)	Caffeine (mg/oz)	Price (cents/oz)	Market share (‰)	Social media WOM brands (1,000)	Social media score
All in sample	1.94	4.17	2.20	2.69	7.70	58.72	0.18
Coca-Cola							
Coke Classic Regular	3.25	4.17	2.92	2.83	31.07	429.80	0.05
Coke Diet	0.00	3.33	3.92	2.90	18.72	89.33	−0.06
Sprite Regular	3.17	5.83	0.00	2.88	8.43	14.33	0.06
Coke Zero Diet	0.00	3.33	2.92	2.97	5.52	14.85	0.01
Fanta Regular	3.67	4.58	0.00	2.61	3.00	30.47	0.42
Pepsi							
Pepsi Regular	3.42	2.50	3.17	2.54	23.64	315.19	0.17
Pepsi Diet	0.00	2.92	2.92	2.65	12.47	11.43	0.05
Mountain Dew Regular	3.83	5.42	4.50	2.81	10.17	47.83	0.06
Sierra Mist Regular	3.25	3.17	0.00	2.54	2.65	3.85	0.34
Mountain Dew Diet	0.00	4.17	4.50	2.77	3.46	3.39	0.40
Mountain Dew CR Reg.	3.75	8.75	4.50	2.71	0.52	0.65	0.17
Sierra Mist Free Diet	0.00	3.17	0.00	2.33	1.06	0.14	0.43
Dr. Pepper							
Dr. Pepper Regular	3.33	4.58	3.50	2.92	6.94	75.15	0.10
Dr. Pepper Diet	0.00	4.58	3.50	2.90	3.22	2.74	0.11
Sunkist Regular	4.17	5.83	3.33	2.53	2.58	4.21	0.36
7 Up Regular	3.17	3.33	0.00	2.53	3.60	13.02	−0.08
7 Up Diet	0.00	5.42	0.00	2.60	1.80	0.31	0.32
Diet Rite Pure Zero Diet	0.00	0.00	0.00	2.46	0.40	0.21	0.33

These are averages across 12 cities and 17 months. The cities are New York, Detroit, Atlanta, Chicago, Los Angeles, Boston, Hartford/New Haven, Syracuse, Dallas, Miami, San Francisco, and Seattle. The months include June 2011 through October 2012. Social media conversations for brand and price are over city-month combinations

Among all brands, Coke Classic Regular enjoys the largest share per market, followed by Pepsi Regular, Coke Diet, and Pepsi Diet.

Columns 7 and 8 of Table 1 report the summary statistics for social media WOM sentiment scores. On average, there are 58,720 conversations about a brand on social media sites in a month. However, the volume of social media WOM varies significantly over brands: Coca-Cola Regular and Pepsi Regular dominate with 429,000 and 315,190 conversations, respectively. Consumers' overall sentiment regarding CSD products is positive. The average social media sentiment score of a CSD brand is 0.18. It should be noted that the sentiment scores for the most popular brands (Coca-Cola Regular, Coca-Cola Diet, Pepsi Diet) are not high because of the large volume of mixed sentiment for them.

3 Empirical model

To assess the impact of social media on consumer demand, a random coefficient logit model of consumer demand is estimated, following Berry, Levinsohn, and Pakes (1995; hereafter BLP). Assume that there is a total number of J CSD products on the market. Use $j=1,\ldots,$ where J denotes a CSD product in the sample and $j=0$ to denote the outside products in the beverage market. The conditional indirect utility of consumer i from purchasing CSD j in market m is

$$\begin{aligned} U_{ijm} = {} & \alpha_i p_{jm} + \beta_i x_j + \gamma_i \mathrm{Lexis}_m + \phi_{1i}\mathrm{SM}_{jm}^{brand} + \phi_{2i}\mathrm{SMScore}_{jm}^{\mathrm{brand}} + \kappa_{1i}\mathrm{SM}_m^{\mathrm{nutrition}} \times x_j \\ & + \kappa_{2i}\mathrm{SMScore}_m^{\mathrm{nutrition}} \times x_j + \mu_1 \mathrm{Dummy}_{\mathrm{Season}} + \mu_2 \mathrm{Dummy}_{\mathrm{DMA}\times\mathrm{SM}}\xi_{jm} \\ & + \varepsilon_{ijm} = \delta_{jm} + \mu_{ijm} + \varepsilon_{ijm} \end{aligned} \tag{1}$$

where p_{jm} is the unit price per ounce of CSD brand j in market m, x_j=(sugar$_j$, sodium$_j$, caffeine$_j$) is a vector of observed nutritional characteristics of CSD brand j, and ξ_{jm} is unobserved product characteristics.[5] Lexis$_m$ is the general media coverage goodwill that captures health information received by consumers. Social media goodwill enters the utility functions directly: $\mathrm{SM}_{jm}^{\mathrm{brand}}$ is the social media WOM that captures all conversations and communications mentioning CSD brand j; $\mathrm{SMScore}_{jm}^{\mathrm{brand}}$ is the social media score of product j in market m. $\mathrm{SM}_m^{\mathrm{nutrition}}=(\mathrm{SM}_m^{\mathrm{sugar}},\mathrm{SM}_m^{\mathrm{caffeine}})$ is a vector capturing all conversations about nutritional factors.[6] The interaction terms $\mathrm{SM}_m^{\mathrm{nutrition}}$ and product characteristics x_j will indicate how those social media conversations on nutritional factors affect consumers' preferences. $\mathrm{SMScore}_m^{\mathrm{nutrition}}$ is a vector of social media scores of the nutritional factors. $\mathrm{Dummy}_{\mathrm{Season}}$ is a vector of season dummy variables and $\mathrm{Dummy}_{\mathrm{DMA}\times\mathrm{SM}}$ is a vector of dummy variables that captures the interaction of DMA and social media volume.

Following Dubé, Hitsch, and Manchanda (2005), social media exposure is modeled as goodwill in order to capture the carry-over effects on demand, following a distributed lag form:

$$\mathrm{SM}_{jt}^{\mathrm{brand}} = \textstyle\sum_k^K = 0\lambda^k \psi\left(\mathrm{sm}_{j,t-k}^{\mathrm{brand}}\right) \tag{2}$$

where $\psi(.)$ is a social media goodwill production function, $\mathrm{sm}_{jt}^{\mathrm{brand}}$ is the number of conversations mentioning CSD brand j at time t, λ is a geometric decay factor, and t and k denote time periods. $\mathrm{SM}_m^{\mathrm{nutrition}}$ and Lexis$_m$ are modeled in a similar way.[7]

$$\mathrm{SM}_t^{\mathrm{sugar}} = \textstyle\sum_k^K = 0\lambda^k \psi\left(\mathrm{sm}_{t-k}^{\mathrm{sugar}}\right) \tag{3}$$

$$\mathrm{SM}_t^{\mathrm{caffeine}} = \textstyle\sum_k^K = 0\lambda^k \psi\left(\mathrm{sm}_{t-k}^{\mathrm{caffeine}}\right) \tag{4}$$

[5] Calories are also an important nutritional factor for CSDs. However, since calories are highly correlated with sugar, with a correlation coefficient of 0.9995, we do not include calories in the analysis.

[6] Since conversations on sodium were too few to be of statistical value in the empirical model, we do not include them in the analysis.

[7] Since the only variation for $\mathrm{SM}_m^{\mathrm{nutrition}}$ and Lexis$_m$ is time, which is included in m, we use only t to denote the subscript in Eqs. 3, 4, and 5.

$$\text{Lexis}_t = \sum_k^K = 0\lambda^k \psi(\text{lexis}l_{t-k}) \tag{5}$$

where $\text{sm}_{t-k}^{\text{sugar}}$ and $\text{sm}_{t-k}^{\text{caffeine}}$ are the total number of conversations mentioning sugar and caffeine, respectively, and Lexis_{t-k} is the number of articles and transcripts on CSD and health from LexisNexis Academic. In this analysis, we use a 2-month period to construct the carry-over effect.

To capture the heterogeneity of consumer preferences, we model the distribution of consumers' taste parameters θ_i=(α_i, β_i, γ_i, ϕ_i, κ_i,μ) as multivariate normal distributions: θ_i=θ+$\Sigma\nu_i$, where Σ is a scaling matrix and ν_i is the unobserved household characteristics, assumed to have a standard multivariate normal distribution. The indirect utility U_{ijm} can be decomposed into three parts: (1) a mean utility term $\delta_{jm}=\alpha p_{jm}+\ \beta x_j+\gamma\text{Lexis}_m+\phi_1\text{SM}_{jm}^{\text{brand}}+\phi_2\text{SMScore}_{jm}^{\text{brand}}+\ \kappa_1\text{SM}_m^{\text{nutrition}}\times x_j+\ \kappa_2\text{SMScore}_m^{\text{nutrition}}\times x_j+\ \mu_1\text{Dummy}_{\text{Season}}+\mu_2\text{Dummy}_{\text{DMA}\times\text{SM}}+\xi_{jm}$, which is common to all consumers; (2) brand-specific and consumer-specific deviations from that mean $\mu_{ijm}=(p_{jm},x_j,\ \text{Lexis}_m,\text{SM}_{jm}^{\text{brand}},\ \text{SMScore}_{jm}^{\text{brand}},\text{SM}_m^{\text{nutrition}}\times x_j,$ $\text{SMScore}_{jm}^{\text{nutrition}}\times x_j)\times(\Sigma\upsilon_i)$, which includes interactions between product characteristics and idiosyncratic taste deviations; and (3) ε_{ijm}, a stochastic term with zero mean, which is distributed independently and identically as a type I extreme value. When a consumer purchases a unit of a brand in the set or the outside good, the probability that consumer i purchases a unit of brand j in market m is

$$s_{ijm} = \frac{\exp\left(\delta_{jm} + \mu_{ijm}\right)}{1 + \sum_{r=1}^{J} \exp(\delta_{rm} + \mu_{irm})} \tag{6}$$

Aggregating over consumers, the market share of product j corresponds to the probability that product j is chosen in market m. Following BLP, matching the predicted market shares with observed ones, we solve for the model parameters using the generalized methods of moments. The estimated coefficients are then used to evaluate how consumers' preferences are affected by social media conversations.

We assume that the product nutritional characteristics are exogenously determined, but the prices are correlated with the unobserved product characteristics or demand shocks. To handle endogeneity of prices, we use two sets of instrumental variables, following previous BLP studies. The first set consists of cost shifters, such as aluminum and raw sugar prices. The second consists of Hausman (1994) type instruments, e.g., prices of the same brand in other markets. The underlying rationale 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. In addition, since it is also possible that the social media conversations are correlated with unobserved demand shocks (and thus are endogenous), we use the total number of Twitter users as an instrument. The number of Twitter users is highly correlated with the volume of conversations on social media sites but not likely to impact the demand of CSD directly.

4 Empirical results

4.1 Econometric results

Table 2 presents the estimated demand parameters taking into account social media conversations about product characteristics and brands. Columns 2 and 3 provide the means and standard errors of the parameters denoting the mean preference of consumers, and columns 4 and 5 provide the standard deviations of the random coefficients that capture the heterogeneity of consumer preferences.

As expected, the estimate of the price coefficient is negative (−0.449) and strongly significant. On average, consumers have a positive and significant valuation of caffeine content but generally dislike sodium. Consumers' preference for sugar is negative but not statistically significant. The standard deviations of the coefficients of sugar and sodium are all significant, suggesting that consumers have heterogeneous preferences for nutritional content in CSD. The coefficient for Lexis media coverage goodwill is negative and significant, suggesting that the general media coverage on CSDs and health-related issues have a significant negative impact on CSD consumption over time. The season dummies show that consumers have a higher demand for CSDs in summer and fall quarters.

Table 2 Demand estimates of consumer preference in the CSD market

	Mean preference		Deviations	
	Mean	SE	Mean	SE
Price	−0.449***	0.156	0.376***	0.110
Sugar	−0.074	0.126	−0.751***	0.080
Sodium	−0.249***	0.034	−0.341***	0.031
Caffeine	0.309***	0.119	−0.116	0.127
Lexis health media coverage	−2.137***	0.210	−1.242*	0.751
Social media brand	4.599***	0.445	0.691*	0.416
Social media brand score	−0.297	0.384	0.102	0.304
Social media sugar×sugar	−45.284***	3.776	47.556***	1.325
Social media caffeine×caffeine	−7.717***	3.839	0.358	4.324
Social media sugar score×sugar	0.037	0.070	−0.360	0.347
Social media caffeine score×caffeine	0.050	0.343	−1.327*	0.794
Constant	−4.603***	0.780	−0.453	0.444
Season summer	0.681***	0.182		
Season fall	0.741***	0.226		
Season winter	0.636***	0.160		
DMA social media interaction dummies	Yes			

The p value of the first stage F statistics is 0.000 and p value of the Hansen J statistic is 0.398

SE standard error

***p<0.01; **p<0.05; *p<0.1

Conversations about specific brands (social media brand) raise consumer awareness about those brands, resulting in a significant positive valuation of the subject brands. The estimated coefficients for the two interaction terms (social media sugar×sugar and social media caffeine×caffeine) capture the impact of social media WOM regarding sugar and caffeine on consumers' preference for a CSD product's nutritional content. Conversations about sugar lower consumer valuation of sugary CSDs; that is, the higher the volume of WOM about sugar, the lower the demand for sugary CSDs. Caffeine conversations also have a negative and significant effect on the valuation of caffeine content. One may conclude that consumer conversations could have a powerful effect on consumer choices of CSD brands with a configuration of characteristics more acceptable to consumers with a greater exposure to social media WOM.

We also include consumers' sentiment regarding specific CSD products and their nutritional content. A high social media score means a more positive sentiment regarding the product, which may potentially amplify the impact of WOM on consumer preferences. However, the effect is not statistically significant. This result suggests that in terms of consumer preferences for CSDs, what really matters is the volume of the social media WOM rather than the sentiment. Likewise, for nutritional characteristics, the social media sentiment scores do not have a significant impact on consumer valuation for sugar and caffeine. Finally, the interaction dummy variables of DMA and social media volume are also included. Overall, there are only slight differences in consumer demand across different DMAs. [8]

4.2 Counterfactual simulations

In this section, we consider the effects of alternative scenarios on CSD consumption by simulating the market outcomes over the sample period. Specifically, we conduct the following three sets of counterfactual simulations to examine how consumers' consumption of CSDs might be affected by different policies:

1. No specific social media conversations on each brand: setting the brand social media goodwill for all CSD products to zero ($SM_{jm}^{brand}=0$, and thus, $SMScore_{jm}^{brand}=0$) while assuming other variables at constant levels.
2. A national health campaign on CSDs, which leads to increasing discussion of sugar on social media sites, assuming the total social media conversations regarding sugar is increased by 10 % (SM_{m}^{sugar} increased by 10 %).
3. No social media conversations regarding caffeine $\left(SM_{m}^{caffeine} = 0, \text{ and thus } SMScore_{jm}^{caffeine} = 0\right)$.

Using the demand estimates, we recalculate new market shares for each CSD brand using the changed product characteristics under different scenarios. The results of the policy simulations are shown in Table 3. S0 is the benchmark scenario, denoting the status quo. The first scenario (S1) assumes no specific social media conversation on any brands on social media sites. Results in Table 3 show that two major brands, Coke

[8] We do not report here the full results on the dummy variables due to space limitation. The full results are available upon request.

Table 3 Simulated market shares under different scenarios

	Base share (‰)	Simulated market shares (‰)			Percentage change (%)		
	S0	S1 No brand SM	S2 Sugar SM volume increased by 10 %	S3 No caffeine SM	S1 No brand SM	S2 Sugar SM volume increased by 10 %	S3 No caffeine SM
Coca-Cola							
Coke Classic Regular	30.13	28.43	29.99	30.14	−5.62	−0.45	0.04
Coke Diet	18.12	18.17	18.10	18.10	0.27	−0.14	−0.10
Sprite Regular	8.13	8.24	8.16	8.12	1.32	0.34	−0.14
Coke Zero Diet	5.46	5.49	5.45	5.45	0.62	−0.08	−0.11
Fanta Regular	3.10	3.09	3.03	3.09	−0.38	−2.34	−0.22
Pepsi							
Pepsi Regular	22.82	21.81	22.54	22.81	−4.43	−1.22	−0.04
Pepsi Diet	12.01	11.96	11.98	12.01	−0.40	−0.26	0.01
Mountain Dew Regular	9.92	10.28	9.81	9.91	3.67	−1.08	−0.01
Sierra Mist Regular	2.46	2.48	2.45	2.46	0.69	−0.51	0.00
Mountain Dew Diet	3.38	3.29	3.36	3.38	−2.69	−0.51	0.12
Mountain Dew CR Reg.	0.53	0.56	0.54	0.53	4.26	1.54	0.15
Sierra Mist Free Diet	1.03	0.95	1.03	1.03	−7.72	−0.11	−0.03
Dr. Pepper							
Dr. Pepper Regular	6.80	7.09	6.77	6.80	4.21	−0.40	−0.08
Dr. Pepper Diet	3.10	3.09	3.09	3.09	−0.31	−0.17	−0.17
Sunkist Regular	2.60	2.72	2.53	2.60	4.48	−2.83	−0.06
7 Up Regular	3.56	3.58	3.56	3.56	0.41	−0.13	0.03
7 Up Diet	1.80	1.71	1.79	1.80	−4.97	−0.19	0.04
Diet Rite Pure Zero Diet	0.39	0.36	0.39	0.39	−7.79	−0.07	0.03

Classic Regular and Pepsi Regular, would experience large decreases in market shares, −5.62 and −4.43 %, respectively. This is intuitive since these two brands are the most active and frequently mentioned on social media, compared to other brands. Contrarily, some other brands, such as Mountain Dew Regular and Sprite Regular, would enjoy a slight increase in market shares. The second scenario (S2) assumes a national health campaign and thus higher level of discussions about sugar content on social media sites. As a result, all but two CSD brands would have decreased market shares, the regular sugary CSDs suffering a larger loss in market shares compared to sugar-free diet ones. The third scenario (S3) assumes zero conversations about caffeine on social media sites. The results indicate a slight change of market shares for most brands. Specifically, there is a slight decrease for with zero caffeine content brands (e.g., Sprite Regular, Fanta Regular, 7 Up Regular, etc.).

5 Discussion

5.1 Conclusions

Building on prior literature, this article has developed a model that explains the role of social media conversations in consumer brand choices. In this model, we account for WOM and consumer sentiment expressed on social media regarding different brands and nutritional content affect consumers' preference and brand choices in the CSD market. Importantly, our study shows that consumer exposure to WOM on various social media sites can be a significant driver of consumer purchasing behavior. Further, consumers' conversations about brands and nutritional aspects of CSDs have a significant impact on their preferences. However, the volume of WOM rather than the sentiment is what matters the most. This has important implications not only for firm strategy but also for public health policy aimed at influencing consumer diets.

5.2 Managerial implications

For managers, our results suggest that firms that want to make use of social media WOM about their products should actively monitor or even spur more conversations about their brands on various social media sites. A successful social media campaign will increase the exposure and awareness of a brand and create more buzz on social media sites, which will lead to a greater probability of a product being chosen by consumers. For example, after the Coca-Cola Company initiated its "Share A Coke" social media campaign on Facebook in 2011, which gave people the chance to order personalized Coke bottles through a Facebook app, the traffic on the Coke Facebook site increased by 870 %. This noteworthy social media campaign earned a total of more than 18 million media impressions and led to a 7 % increase in sales (Moth 2013).

Another managerial implication is that consumers' conversations on social media signal their preferences for product characteristics. Given the lower cost of information conveyed through the Internet and social media in particular, consumers now pay more attention to the nutritional content of food and beverage products. It is therefore important to monitor consumers' attitudes and sentiments regarding product attributes.

This presents both challenges and opportunities for managers to reformulate their existing products and design new products and marketing campaigns in time to keep up with the growing and changing consumer preferences that are in part driven by social media WOM.

From a public health policy perspective, our results suggest that a national public health campaign that raises consumer conversations about sugar, for example, can be effective in decreasing the consumption of high-caloric, sugary CSDs.

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References

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica, 63*, 841–89.

Bruce, N., Foutz, N., & Kolsarici, C. (2012). Dynamic effectiveness of advertising and word of mouth in sequential distribution of new products. *Journal of Marketing Research, 49*, 469–486.

Chan, T. Y. (2006). Estimating a continuous hedonic-choice model with an application to demand for soft drinks. *RAND Journal of Economics, 37*(2), 466–482.

Dubé, J., Hitsch, G., & Manchanda, P. (2005). An empirical model of advertising dynamics. *Quantitative Marketing and Economics, 3*, 107–144.

Financial Times Special Report, 2012. Digital and social media marketing. March 7, 2012, www.ft.com/digital-social-media-marketing-2012

Forbes, 2013, Coca-Cola leveraging social to drive leadership in social media marketing. June 18, 2013, http://www.forbes.com/sites/siliconangle/2013/06/18/coca-cola-leveraing-social-to-drive-leadership-in-social-media-marketing/

Goldfarb, A., & Tucker, C. (2011). Substitution between offline and online advertising markets. *Journal of Competition Law and Economics, 7*, 37–44.

Hausman, J. 1994. Valuation of new goods under perfect and imperfect competition (NBERWorking Paper). Retrieved March 3, 2014 from http://www.nber.org/papers/w4970.pdf

Hoffman, D. L., & Fodor, M. (2010). Can you measure the ROI of your social media marketing? *MIT Sloan Management Review, 52*, 41–49.

Liebowitz, S. J., & Zentner, A. (2012). Clash of the titans: does Internet use reduce television viewing? *Review of Economics and Statistics, 94*, 234–245.

Liu, Y., R.A. Lopez, and C. Zhu. 2014. The impact of alternative policies to decrease soda consumption. *Agricultural and Resource Economics Review,* 43(1), Forthcoming.

Lopez, R. A., & Fantuzzi, K. (2012). Demand for carbonated soft drinks: implications for obesity policy. *Applied Economics, 44*, 2859–2865.

Moth, D., 2013. 10 inspiring digital marketing campaigns from Coca-Cola, http://econsultancy.com/us/blog/63175-10-inspiring-digital-marketing-campaigns-from-coca-cola

Onishi, H., & Manchanda, P. (2012). Marketing activity, blogging and sales. *International Journal of Research in Marketing, 29*, 221–234.

Orlov, E. (2011). How does the internet influence price dispersion? Evidence from the airline industry. *Journal of Industrial Economics, 59*, 21–37.

Reuters, 2012. U.S. soda consumption fell faster in 2011, http://www.reuters.com/article/2012/03/20/drinks-idUSL1E8EK1P620120320

Rui, H., Liu, Y., & Whinston, A. B. (2013). Whose and what chatter matters? The impact of tweets on movie sales. *Decision Support Systems, 55*(4), 863–870.

Shweidel, D.A., W.W. Moe, and C. Boudreaux. 2011. Social media intelligence: measuring brand sentiment from online conversations. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1874892

Smith, M., & Telang, R. (2010). Piracy or promotion? The impact of broadband Internet penetration on DVD sales. *Information Economics and Policy, 22*, 289–298.

Trusov, M., Bucklin, R., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: findings from an Internet social networking site. *Journal of Marketing, 73*, 90–102.

Zmuda, N., 2012. Soft-drink sales dip to 1996 levels, *Advertising Age*, http://adage.com/article/news/softdrinkscontinuedeclinesales1996 levels/233414/