The Impact of Social Media on Consumer Demand: The Case of Carbonated Soft Drink Market

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Abstract

This article estimates the impact of social media exposure on consumer valuation of product characteristics. We apply the Berry, Levinsohn and Pakes (1995) model of market equilibrium to sales data for 18 carbonated soft drink brands sold in 12 cities over 17 months (June 2011 to October 2012) and social media conversations on Facebook, Twitter and YouTube. Empirical results show that social media exposure is a significant driver of consumer behavior through altering evaluation of product characteristics and purchase choices.

Keywords: Social Media, Demand, Consumer behavior, Internet, Carbonated soft drinks

JEL Classification: D12, M37, L66

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1. Introduction

The recent growth of social media like Facebook, Twitter and YouTube has significantly changed the nature of communication from unidirectional to bidirectional, not only between firms and consumers but also among consumers. Typical Americans now spend approximately 20% of their time online on social media networks (Nielsen, 2010). From soft drinks to breakfast cereals, to travel, to electronics, to restaurant recommendations, word of mouth and social media have been identified as the leading sources for purchase referrals for consumer products and have become key drivers of brand recommendations, loyalty, and new customer acquisition (Hoffman and Fodor, 2010).

Previous economic studies have focused on the effects of internet penetration and the interaction between online and offline advertising (Smith and Telang, 2010; Goldfarb and Tucker, 2011; Orlov, 2011; Liebowitz and Zentner, 2012). To date, there are few studies that have examined the influence of social media on sales (Rui, Liu, and Whinston, 2013; Onishi and Manchanda, 2012; Bruce, Foutz, and Kolsarici, 2012), but there are no studies that formally examine its impact on consumer demand.

This article presents estimates of the impact of social media exposure on demand, using carbonated soft drinks (CSDs) as a case study. Understanding how social media affects consumer valuation of CSD product characteristics is useful not only for designing private strategies to stimulate demand but also for informing public policies aimed at regulating advertising in the internet age (U.S. Food and Drug Administration, 2011; Thomaselli, 2011).

2. Empirical Model

Following Berry, Levinsohn and Pakes (1995; hence BLP), assume a consumer chooses a CSD brand among competing products (or an outside good) and maximizes utility, given social media exposure as well as product and his/her own characteristics. The conditional indirect utility of consumer i from purchasing CSD product j in market m is

$$U_{ijm} = \alpha_i p_{jm} + \beta_i x_j + \gamma_i SM_{jm}^{brand} + \phi_{1i} SM_{jm}^{price} \times p_{jm} + \phi_{2i} SM_m^{nutrition} \times x_j + \xi_{jm} + \varepsilon_{ijm} = \delta_{jm} + \mu_{ijm} + \varepsilon_{ijm} \quad (1)$$

where p_{jm} is the unit price per oz of a CSD brand j in market *m*;. $x_j = (sugar_j, caffeine_j, sodium_j)$ is a vector of observed nutritional characteristics of CSD brands (as in Lopez and Fantuzzi, 2012); and ξ_{jm} is unobserved product characteristics. Social media goodwill enters the utility functions directly: SM_{jm}^{brand} is the social media exposure which captures all conversations and communications mentioning CSD brand *j*; SM_{jm}^{price} captures all conversations about CSD brand *j*'s prices on social media, and $SM_m^{nutrition} = (SM_m^{sugar}, SM_m^{caffeine}, SM_m^{sodium})$ is a vector capturing all conversations about nutritional factors.

Following Dubé et al. (2005), social media exposure is modelled as goodwill in order to capture the carry-over effects on demand, following a distributed lag form:

$$SM_{jt}^{brand} = \sum_{k=0}^{K} \lambda^k \psi(sm_{j,t-k}^b) \quad (2)$$

where $\psi(.)$ is a social media goodwill production function; sm_{jt}^b 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. SM_{jm}^{price} and $SM_m^{nutrition}$ were modeled in a similar way. Since there were only a few sodium conversations, they were dropped from the model.

The indirect utility u_{ijm} can be decomposed into three parts: (1) a mean utility term δ_{jm}, which is common to all consumers; (2) brand-specific and consumer-specific deviations from that mean μ_{ijm}, 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. To complete the model and to define the market, an outside good is included to give the consumer the possibility not to buy any of the brands included in the choice set.

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,

$$s_{ijm} = \frac{\exp(\delta_{jm}+\mu_{ijm})}{1+\sum_{r=1}^{J} exp(\delta_{rm}+\mu_{irm})} \quad . \tag{3}$$

Aggregating over consumers, the market share of the j^{th} brand corresponds to the probability that the j^{th} brand is chosen in market *m*. Following BLP, matching the predicted market shares with observed ones, we solve for the model parameters using GMM. The estimated coefficients are then used to evaluate how consumers' preferences are affected by social media exposure.

Two Nielsen datasets were matched by months and cities: (1) the new Nielsen social media dataset that includes conversations among consumers on Facebook, Twitter and YouTube, and (2) Nielsen Scantrack data on soda sales and prices. After dropping two months due to the lags in equation (2), the resulting dataset encompassed 17 months (June 2011 to October 2012) over 12 cities (New York, Detroit, Atlanta, Chicago, Los Angeles, Boston, Hartford/New Haven, Syracuse, Dallas, Miami, San Francisco, and Seattle). Most social media conversations involved specific brands and sugar and caffeine content, with sparing conversations about price and no conversations about sodium (Table 1). The resulting dataset includes 3,672 CSD brand observations (18 brands x 12 cities x 17 months). CSD company and city fixed effects were included to control for unobserved variables. The results are presented below.

3. Results and Discussion

Table 2 presents the estimated demand parameters taking into account social media conversations about product characteristics and brands. Exposure to social media has a significant impact on consumers' valuation of CSD characteristics. More specifically, conversations about specific brands raise consumer awareness about those brands, resulting in a significant positive valuation of the subject brands. Conversations about sugar lowers consumer valuation of sugary CSDs. This is important from a health perspective as sugary CSDs have been identified as an important contributor to the ongoing obesity epidemic. Likewise, caffeine conversations also have a negative effect on the valuation of CSDs. If so, consumer conversations can have a powerful effect on consumer demand for CSDs and the configuration of characteristics more acceptable to consumers exposed to social media.

It is also interesting to note that exposure to social media does not have a significant effect on the negative response to price. A possible explanation is that consumers are not interested in discussing prices as CSDs are characterized by non-price competition so that the role of price is negated in terms of marketing these products.

For consumers not exposed to social media, the results indicate that they value sugar content more positively, which translates into having a preference for taste over nutrition. They also value caffeine content more positively than consumers exposed to social media. It is also interesting to note that Coca Cola products are valued well above products of other CSD companies, with PepsiCo being second and Dr. Pepper third.

4. Conclusions

Consumer exposure to social media can be a significant driver of consumer behavior through referrals and increased awareness. In terms of the results of this paper, consumer conversations about brands and nutritional aspects of carbonated soft drinks have a significant impact on their choices. This has important implications not only for firm strategy but also for those interested in public health policy aimed at improving consumer diet.

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Table 1. Summary Statistics: Averages across Cities and Months

Brand	Sugar	Sodium	Caffeine	Price	Market Shares	SM Brands	SM Price
	(g/oz)	(mg/oz)	(mg/oz)	(cents/oz)	(‰)	(1,000)	(1,000)
Coca Cola							
Coke Classic Regular	3.25	4.17	2.92	2.83	31.07	429.80	2.54
Coke Diet	0.00	3.33	3.92	2.90	18.72	89.33	0.18
Sprite Regular	3.17	5.83	0.00	2.88	8.43	14.33	0.11
Coke Zero Diet	0.00	3.33	2.92	2.97	5.52	14.85	0.04
Fanta Regular	3.67	4.58	0.00	2.61	3.00	30.47	0.12
Pepsi							
Pepsi Regular	3.42	2.50	3.17	2.54	23.64	315.19	1.30
Pepsi Diet	0.00	2.92	2.92	2.65	12.47	11.43	0.06
Mountain Dew Regular	3.83	5.42	4.50	2.81	10.17	47.83	0.10
Sierra Mist Regular	3.25	3.17	0.00	2.54	2.65	3.85	0.03
Mountain Dew Diet	0.00	4.17	4.50	2.77	3.46	3.39	0.01
Mountain Dew CR Reg.	3.75	8.75	4.50	2.71	0.52	0.65	0.00
Sierra Mist Free Diet	0.00	3.17	0.00	2.33	1.06	0.14	0.00
Dr. Pepper							
Dr Pepper Regular	3.33	4.58	3.50	2.92	6.94	75.15	0.28
Dr Pepper Diet	0.00	4.58	3.50	2.90	3.22	2.74	0.01
Sunkist Regular	4.17	5.83	3.33	2.53	2.58	4.21	0.09
7 Up Regular	3.17	3.33	0.00	2.53	3.60	13.02	0.11
7 Up Diet	0.00	5.42	0.00	2.60	1.80	0.31	0.01
Diet Rite Pure Zero Diet	0.00	0.00	0.00	2.46	0.40	0.21	0.01

Note: 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. Social media conversations about sugar and caffeine averaged 13,610 and 6,550 per city-month observation and are not brand-specific.

Table 2. Estimated Demand Parameters

	Mean Utility		Deviations	
	Mean	Std.Err	Mean	Std.Err
Prod Characteristics				
Price	-1.768	0.261	2.849	0.235
Sugar	0.620	0.106	-0.569	0.316
Sodium	-0.284	0.043	0.741	0.116
Caffeine	0.757	0.099	-0.032	0.245
Social Media Exposure				
Social Media Brands	1.930	0.628	-2.828	1.023
Social Media Sugar * Sugar	-0.025	0.003	-0.086	0.005
Social Media Caffeine * Caffeine	-0.018	0.003	0.014	0.007
Social Media Price * Price	-0.811	4.045	-6.809	7.560
Fixed Effects				
Constant	-7.487	0.786	-16.521	0.339
Coca Cola	1.467	0.162		
Pepsi	0.027	0.140		
DMA Dummies	Yes			
Month Dummies	Yes			