Consumer Engagement, Attention, and Market Shares:Evidence from the Carbonated Soft Drinks Market

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PRELIMINARY AND INCOMPLETE

Abstract

Social media platforms facilitate a real-time "two-way" communication channels among consumers and between consumers and brands. Social media users can now interact with brands directly through Facebook and Twitter. These new features make social media a very distinctive class of online WOM. In this paper, we formulate a random coefficient discrete choice model of consumer demand to study whether and how consumer engagement and attention on the Internet affect the consumption of carbonated soft drinks (CSDs). We model consumer attention and engagement on social media as goodwill in order to capture the carry-over effects of WOM's impact on demand and combine two types of product level data: monthly CSD sales data and social media data. Our results suggest that the three types of social media messages all have significant and positive effects on CSD demand. In particular, indirect engagement on Twitter has the largest impact on consumer demand, followed by direct engagement on Twitter and consumer engagement on Facebook.

Keywords: Consumer Engagement, Social Media, Consumer Demand

1 Introduction

Since the Internet revolution, online Word-of-mouth (WOM) has assumed a prominent role both in people's everyday purchase decisions. Consumers today rely more and more on various sources of online WOM to decide which brand of consumer products to buy, which restaurants to go, or even which doctors to visit. In response to the popularity of online WOM, numerous studies have examined the effect of online WOM on movie box office revenues (Chintagunta, Gopinath and Venkataraman, 2010; Rui, Liu and Whinston, 2013), on TV ratings (Godes and Mayzlin, 2004), on book sales (Chevalier and Mayzlin, 2006), etc.

In recent years, the landscape of online word of mouth has been significantly changed by the rise of social media platforms such as Facebook and Twitter. Unlike the traditional online product review sites where product reviews are infrequently posted at various places and are later pulled by consumers when they actively search for reviews on products of their interests, social media users post and pass messages to friends or followers in a much more *interactive* and *real-time* fashion. Moreover, social media users also interact with brands directly through Facebook and Twitter. The "real-time" and "interactive" features make social media a very distinctive class of online WOM. This is probably particularly important to the carbonated soft drinks (CSD) industry as consumers' purchase decisions of such product are more impulsive and rely much less on product review information (Pinantoan, 2011).

Another important factor that may reflect consumers' interest in a particular brand is how often the brand name is searched which can be captured by the Google trends search index given the dominant role Google plays in the Internet search industry. Google Trends search index measures the frequency of a given keyword being searched in a given region over a given period of time and the search index is available almost in real time. Indeed, there

are a plethora of papers using Google Trends to nowcast or forecast real world events, with Google Flu Trends being the most well-known example.[1] We consider consumers' attention to brands (measured by google search index) as a passive form of social media, in contrast to active forms of social media such as consumers' engagement with brands on Twitter and Facebook.

The goal of this paper is to study whether and how these two forms of social media (active engagement and passive attention) associated with a brand affect its market share. To adapt to the unique features of social media, we distinguish social media messages based naturally on the social media platforms and how they are used by users. For example, we identify *direct engagement* messages as social media content directly (and publicly) sent to brands by consumers and we identify *indirect engagement* messgages as social media content containing brand related hashtags. Among direct engagement message, we differentiate those on Facebook from those on Twitter.

We focus on the CSD industry because the major players (Cocacola and Pepsi) enjoy well-established brand names and are very active on social media. To study the effect of social media on CSD consumption, we combines two types of product level data: monthly CSD sales data and social media data. The monthly data on CSD sales, collected by the Nielsen Company, cover 4 designated market areas (DMAs) from January 2011 to October 2012. The social media data is collected from Twitter, Facebook, and Google for the same period.

We formulate a random coefficient discrete choice model of consumer demand to capture the heterogeneity of consumer preferences. Following Nerlove-Arrow (1962), consumer attention and engagement on social media is modelled as goodwill in order to capture the carry-over effects of WOM's impact on demand. We then constructed our model from the conditional indirect utility of consumer purchasing each type of product.

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[1]https:www.google.orgflutrendsus/#US

Our results suggest that the three types of social media messages all have significant and positive effects on CSD demand. In particular, indirect engagement on Twitter has the largest impact on consumer demand, followed by direct engagement on Twitter and consumer engagement on Facebook.

The rest of the paper is organized as follows. We first describe all sources of data we used in Section 2. We then introduce the model and estimation in Section 3, and present our empirical findings in Section 4. In Section 5, we present the managerial implications and discussions of this study, and then conclude.

2 Data

This analysis combines two types of product level data: monthly CSD sales data and social media data. The monthly data on CSD sales, collected by the Nielsen Company, cover 12 DMAs from January 2011 to October 2012, including Atlanta, Boston, Chicago, Dallas, Detroit, Hartford, Los Angeles, Miami, New York, San Francisco, Seattle, and Syracuse. These data include market level sales data for supermarkets with more than $2 million annual sales, which consists of dollars sales, volume sales, and prices for 18 diet and regular CSDs. Of these 18 products, 5 are owned by Coca Cola; 7 are owned by Pepsi; and 6 are owned by Dr.Pepper. The dataset contains information on product characteristics (e.g. nutrition content and package), marketing (e.g. price and in-store displays), location, and time of each purchase. The richness of the data allows us to capture price and packaging variation of various national brand and private label soft drinks while controlling time, markets, and product characteristics.

Our social media data is collected from three different sources: Twitter, Facebook, and Google Trends. Twitter data is collected from Twitter public streams, which is a real-time

random sample of all tweets generated.[2] From the sample, we match those tweets containing keywords that we are interested in and aggregrate them to monthly level. Google Trends data is downloaded from Google and then transformed so that the search index is comparable across keywords, cities, and time.

We also collect data of consumer engagement on Facebook for a brand. Not all brands have a Facebook page. Therefore, in our data, 12 out of 18 brands have its own official Facebook page. For each posts by the page, the consumers can either click the "like" button if they read it and find it interesting, write down their "comments" under the posts, or "share" the post with their friends on their own Facebook pages. Either way, the consumers are actively engaging and interacting with the brands. Specifically, we collect the number of "like", "comment", and "share" for all posts by the brand from January 2011 to October 2012, and construct a variable "facebook response" by adding all three types together since the majority is "like".

Table 1 reports the summary statistics of the product characteristics of carbonated soft drinks brands. We see that the average amount of calories, sugar and caffeine contained in regular/diet private label and national brand CSDs are similar but national brand CSDs do contain more sodium on average. Table 1 also reports the summary statistics of average unit price and market shares for different brands. The average unit prices are calculated from sales transactions recorded in the data in the 12 DMAs over the 2 years so they are actually market-share weighted. In general, the price of private label products are cheaper than national brands. For example, the average price of Coca Cola regular is 2.83 cents per oz while it costs 2.65 cents per oz for Pepsi Diet.

The market shares of various CSD products reported in Table 1 are calculated by volume sold. The market is defined as a general refreshment beverage market (Chan 2006, Lopez and Fantuzzi 2012). The market size in each market is the total volume consumption of CSD,

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[2]https://dev.twitter.com/docs/streaming-apis/streams/public

Brand	Sugar (g/oz)	Sodium (mg/oz)	Caffeine (mg/oz)	Price (cents/oz)	Mkt Shr ‰
Coca-Cola					
Coca-Cola Regular	3.25	4.17	2.92	2.83	30.91
Coca-Cola Diet	0	3.33	3.92	2.89	18.64
Coca-Cola Zero Diet	0	3.33	2.92	2.97	5.5
Fanta Regular	3.67	4.58	0	2.61	2.96
Sprite Regular	3.17	5.83	0	2.88	8.39
Pepsi					
Pepsi Regualr	3.42	2.5	3.17	2.54	23.52
Pepsi Diet	0	2.92	2.92	2.65	12.42
Mountain Dew Regular	3.83	5.42	4.5	2.81	10.11
Mountain Dew Diet	0	4.17	4.5	2.77	3.44
Mountain Dew Code Red Reg.	3.75	8.75	4.5	2.7	0.52
Sierra Mist Regular	3.25	3.17	0	2.54	2.67
Sierra Mist Free Diet	0	3.17	0	2.33	1.06
Dr. Pepper					
Dr.Pepper Regular	3.33	4.58	3.5	2.92	6.88
Dr.Pepper Diet	0	4.58	3.5	2.9	3.21
7 Up Regular	3.17	3.33	0	2.53	3.57
7 Up Diet	0	5.42	0	2.6	1.79
Sunkist Regular	4.17	5.83	3.33	2.54	2.54
Diet Rite Pure Zero Diet	0	0	0	2.46	0.4

Table 1: Summary Statistics of Product Characteristics

Brand	Twitter Direct Engagement(@)	Twitter Indirect Engagement (#)	Google Trend Search	Facebook Response
Coca-Cola Coca-Cola Regular	2,845	2,772	8.82	192,699
Coca-Cola Diet	2,845	2,772	8.82	17,591
Coca-Cola Zero Diet	2,845	2,772	8.82	0
Fanta Regular	0	0	0	5,360
Sprite Regular	178	415	2.08	51,898
Pepsi				
Pepsi Regualr	2,789	1,342	4.29	175,261
Pepsi Diet	2,789	1,342	4.29	11,495
Mountain Dew Regular	324	0	1.13	83,837
Mountain Dew Diet	324	0	1.13	6,621
Mountain Dew Code Red Reg.	324	0	1.13	0
Sierra Mist Regular	0	0	0	14,218
Sierra Mist Free Diet	0	0	0	0
Dr. Pepper				
Dr.Pepper Regular	734	409	0	519,119
Dr.Pepper Diet	734	409	0	0
7 Up Regular	0	0	0	19,000
7 Up Diet	0	0	0	0
Sunkist Regular	0	0	0	40,011
Diet Rite Pure Zero Diet	0	0	0	0

Table 2: Summary Statistics of Social Media Engagement across Brands

liquid tea, fruit juice, milk, and bottled water, which is calculated as *per capita consumption* × *population.* Therefore, consumers have outside options of not purchasing CSD products. Among all brands, Coke Classic regular enjoys the largest share per market, followed by Pepsi regular, Coke Diet, and Pepsi Diet. It is clear that Coca Cola and Pepsi dominant the CSD market. Table 2 presents the summary statistics of the social media engagement across brands from different sources. It is clear that Coca Cola, Pepsi, and Dr. Pepper are the leaders in terms of the volume of consumer engagement on all three sites.

3   Model

Assume there are a total number of J carbonate soft drink (CSD) product on the market.Use $j = 1, ...J$ to denote a CSD product (e.g., Coca Cola Regular, Pepsi Diet, or Dr. Pepper Regular), and $j = 0$ to denote the general outside product in the beverage market. We define a market as a city-week combination in this analysis.

Following Berry, Levinsohn and Pakes (1995), we specify the conditional indirect utility of consumer i from purchasing CSD j or an outside product in market m as

$$
\begin{aligned}
u_{ijm} &= \alpha_i p_{jm} + \phi_{1i} TwitterDE_{jm} + \phi_{2i} TwitterIE_{jm} + \phi_{3i} GoogleE_{jm} \\
&\quad + \phi_{4i} FacebookE_{jm} + \ x_j \beta_i + \xi_{jm} + \epsilon_{ijm} \qquad (1) \\
&= \delta_{ijm} + \mu_{ijm} + \epsilon_{ijm} \qquad (2)
\end{aligned}
$$

where p_{ijm} is the unit price per oz of a soda drink product j in market m. x_j is a vector of observed nutritional characteristics (sugar, sodium, and caffeine content per oz) of soft drink brands. $Tweet_{jm}$ is the tweet goodwill which capture the effect of the total number of tweets mentioning brand j. $TwitterDE_{jm}$ is the engagement tweet goodwill which captures the effects of total number of tweets with "@ + brand j". $TwitterIE_{jm}$ is the promotion tweet

goodwill which captures the effect of total number of tweets with "# + brand j". $GoogleE_{jm}$ is the google engagement goodwill which captures the volume of consumer online searches of brand j on google. $FacebookE_{jm}$ is the Facebook engagement goodwill which reflects the consumer engagement and responses on brand j's Facebook page. ξ_{jm} is the unobserved product characteristics.

Following Nerlove-Arrow(1962)'s exponential decay goodwill model, social media engagement for each brand is modeled as goodwill in order to capture the carry-over effects of the engagement's impact on demand. Specifically, product j's Tweet direct engagement goodwill stocks in period t is derived in a distributed lag form:

$$TwitterDE_{jt} = \theta TwitterDE_{j,t-1} + \sqrt{direct_{jt}} \tag{3}$$

where θ is the carryover coefficients for brand tweets engagement and the square root captures diminishing effects (Erickson 1992). tw_{jt} represents the total number of engagement tweets with "@ + brand j" mentioning the CSD brand j at time t and t and k denote time periods. In this analysis, Tweet direct engagement goodwill enters the utility functions directly.

Other social media engagement goodwill variables are modeled in a similar way.

$$TwitterIE_{jt} = \theta TwitterIE_{j,t-1} + \sqrt{indirect_{jt}} \tag{4}$$

$$GoogleE_{jt} = \theta GoogleE_{j,t-1} + \sqrt{google_{jt}} \tag{5}$$

$$FacebookE_{jt} = \theta FacebookE_{j,t-1} + \sqrt{facebook_{jt}} \tag{6}$$

where $indirect_{j,t-k}$, $google_{jt}$, and $facebook_{jt}$ are the total number of promotion tweets with "#+brand j" at time t, the total number of google searches of brand j at time t, and the total number of Facebook responses on brand j's Facebook page at time t, respectively.

To capture the heterogeneity of consumer preferences, we model the distribution of con-

sumers' taste parameters, $\theta_i = (\alpha_i, \beta_i, \phi_{1i}, \phi_{2i}, \phi_{3i}, \phi_{4i})$, as multivariate normal distributions.

$$\theta_i = \theta + \Sigma\nu_i \tag{7}$$

where Σ is a scaling matrix and ν_i is the unobserved household characteristics, which is assumed to have a standard multivariate normal distribution. Let

$$
\begin{aligned}
\delta_{jm} &= \alpha p_{jm} + \phi_{1i} TwitterDE_{jm} + \phi_{2i} TwitterIE_{jm} + \phi_{3i} GoogleE_{jm} \\
&\quad + \phi_{4i} FacebookE_{jm} + x_j\beta_i + \xi_{jm} \\
\mu_{ijm} &= (p_{jm}, TwitterDE_{jm}, TwitterIE_{jm}, GoogleE_{jm}, FacebookE_{jm}, x_j)' * (\Sigma\nu_i),
\end{aligned}
$$
(8)
(9)

then the indirect utility U_{ijm} can be decomposed into three parts: a mean utility term δ_{jm}, which is common to all consumers; a brand-specific and consumer-specific deviation from that mean, μ_{ijm}, which includes interactions between consumer and product characteristics; and idiosyncratic tastes, where ϵ_{ijm} is a mean zero stochastic term distributed independently and identically as a type I extreme value distribution.

Assuming an i.i.d type I extreme value distribution of ϵ_{ijm}, we have a closed form solution of the probability a consumer i choosing soft drink j in market m:

$$Pr_{ijm} = \frac{\exp(\delta_{jm} + \mu_{ijm})}{1 + \sum_J exp(\delta_{jm} + \mu_{ijm})}$$

Aggregating over consumers, we can generate the market share of the brand in market m at time t:

$$s_{jm}(\theta) = \int I(\nu_i, \epsilon_{ijm}) : U_{ijm} \geq U_{ihm}, \forall h = 0, ..., J dG(\nu) dF(\epsilon) \tag{10}$$

where θ is a vector of consumer taste parameters as defined previously; $h = 0$ denoted the outside goods, and $G(\nu)$ and $F(\epsilon)$ are the cumulative density functions for the indicated

variables, which is assumed to be independent from each other. Matching the predicted market shares with data, We can solve for $(\alpha, \beta, \phi_1, \phi_2, \phi_3, \phi_4, \Sigma)$ using GMM.

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 several sets of exogenous instrumental variables following Nevo (2000). The first set of instruments is cost shifters, such as raw sugar price, aluminum price, TV advertising cost per second in each city/month etc. We also use Hausman (1996) type instruments, which are prices of the same brand in other markets. The intuition behind is that the prices of the same brand in different markets are correlated due to the common production cost, but uncorrelated with market specific demand shocks.

4   Results

4.1   Demand Estimate

We present the estimates of the demand coefficients in Table 3. Columns 2 and 3 give the means and standard errors of the parameters denoting the mean preference of consumers, or $\alpha, \beta, \phi_1, \phi_2, \phi_3$ and ϕ_4. Columns 4 and 5 provides the standard deviations of the random coefficients that capture the heterogeneity of consumer preferences. As expected, the estimate of the price coefficient is negative (-1.336) and strongly significant. Consumers' preferences of nutritional factors are also given. On average, consumers have a significantly positive valuation of sugar, and hence high calories, of carbonated soft drinks. Besides sugar, consumers also prefer caffeine intake but generally dislikes sodium intake.

The second panel of the table show the impact of all types of online engagement with brands on consumers' demand. Overall, all types of engagement on Twitter, Google, and Facebook have positive and significant impacts on demand, with varying magnitudes. Since the google trend search volume is normalized across all brands and time period, the coefficient

of google trend search is not directly comparable with other three indexes. Among other three indexes, Twitter indirect engagement (# + brand name) has the highest impact, followed by Twitter direct engagement (@ + brand name) and Facebook responses.

	Mean Preference		Std. Deviation	
	Mean	Std.Err	Mean	Std.Err
Product Characteristics				
Price	-1.336	0.124	0.030	0.101
Sugar	0.165	0.022	0.000	0.195
Sodium	-0.110	0.024	0.104	0.028
Caffeine	0.104	0.025	0.025	0.068
Social Media Engagement				
Twitter Direct Engagement(@)	8.211	2.928	0.711	24.588
Twitter Indirect Engagement (#)	24.343	6.224	-7.348	7.889
Google Trend Search	0.041	0.013	0.006	0.038
Facebook Response	1.389	0.178	0.285	0.690
Others				
Constant	-3.221	0.340	-0.101	0.345
Coca Cola	0.715	0.124		
Pepsi	-0.273	0.080		
Month Dummies	Yes			

Table 3: Demand Estimates of Consumer Preferences in the CSD Market

4.2 Counterfactual Simulations

Using the estimated parameters from the demand model, this section considers the effects of alternative consumer engagement levels on CSD demand by simulating the market outcome over the sample period under different scenarios. Specifically, we conduct 12 sets (4 types × 3 companies) of conterfactual simulations to examine how demand and market shares of each CSD brand might be affected by different levels of the four types of consumers engagement with the company (Coca-Cola, Pepsi, and Dr.Pepper):

1. The volumes of direct twitter engagement (@) are increased by 10% for all Coca-Cola

or Pepsi or Dr.Pepper brands, respectively.

2. The volumes of indirect twitter engagement (#) are increased by 10% for all Coca-Cola or Pepsi or Dr.Pepper brands, respectively.

3. The search volume on Google are increased by 10% for all Coca-Cola or Pepsi or Dr.Pepper brands, respectively.

4. The total number of Facebook response are increased by 10% for all Coca-Cola or Pepsi or Dr.Pepper brands, respectively.

We can examine and compare the effects of alternative consumer engagement on brands' market share changes through simulations. Using the demand estimates, we recalculate the new market shares using the changed product characteristics (engagement goodwill) under different scenarios. The results of the conterfactual simulations are presented in Table 4.

The first column, S0, is the benchmark scenario, which demonstrate the status quo. Columns 2 to 5 presents brands' new simulated market shares when the levels of the four types of consumer engagement of its own company are increased. For example, when the volume of direct twitter engagement (@) of Coca-Cola Company is increased by 10%, the new market share for Coca-Cola regular is 30.63‰, and the market share for Coca-Cola diet is 16.37‰. When the consumer response on PepsiCo's Facebook page are increased by 10%, the market share of Pepsi Regular will increase to 15.98‰.

Columns 6 to 9 show the percentage changes of the market shares, compared with benchmark scenario S0. It is interesting to notice that, firms respond differently to different types of consumer engagement. In other words, the consumer engagement effectiveness vary across different types and firms. For example, Coca-Cola regular, Coca-Cola diet, and Coca-Cola Zero respond the most to increases in indirect engagement tweets (#). 10% increase in indirect engagement tweets will push up the market share by over 9% on average. It is the

same story for Pepsi regular and Pepsi Diet, which respond the most to indirect engagement tweets (#). However, increases of consumer responses on Facebook works the best for Mountain Dew regular and increases in google search volume for Mountain Dew Diet. Finally, Dr.Pepper regular enjoy the biggest percentage increase in market share, 10.39%, from 10% increase in consumer responses on Facebook page.

	Base Shares (‰)	Simulated Market Shares (‰)				Percentage Change (%)			
	S0	S1 (@)	S2 (#)	S3 (google)	S4 (FB)	S1 (@)	S2 (#)	S3 (google)	S4 (FB)
Coca-Cola									
Engagement increased by 10%									
Coca-Cola Regular	29.76	30.62	32.58	31.59	30.86	2.88	9.47	6.15	3.70
Coca-Cola Diet	15.91	16.37	17.42	16.86	15.91	2.87	9.45	5.95	0.00
Coca-Cola Zero Diet	4.64	4.78	5.09	4.92	4.63	2.89	9.52	6.06	-0.34
Fanta Regular	3.40	3.39	3.37	3.38	3.39	-0.28	-0.77	-0.50	-0.25
Sprite Regular	7.63	7.63	7.68	7.73	7.68	-0.09	0.56	1.28	0.67
PepsiCo									
Engagement increased by 10%									
Pepsi Regualr	15.59	15.98	16.21	15.98	15.98	2.52	4.01	2.54	2.49
Pepsi Diet	7.51	7.70	7.81	7.69	7.50	2.53	3.99	2.49	-0.09
Mountain Dew Regular	3.94	3.95	3.91	3.97	3.98	0.05	-0.78	0.52	0.98
Mountain Dew Diet	1.53	1.53	1.52	1.53	1.52	0.07	-0.73	0.53	-0.23
Mountain Dew Code Red Reg.	0.25	0.25	0.24	0.25	0.25	0.03	-0.85	0.50	-0.36
Sierra Mist Regular	2.14	2.14	2.13	2.13	2.14	-0.24	-0.62	-0.46	-0.08
Sierra Mist Free Diet	0.89	0.89	0.88	0.88	0.89	-0.25	-0.64	-0.46	-0.26
Dr.Pepper									
Engagement increased by 10%									
Dr.Pepper Regular	9.24	9.29	9.30	9.19	10.20	0.58	0.67	-0.52	10.39
Dr.Pepper Diet	3.39	3.41	3.41	3.37	3.37	0.58	0.68	-0.50	-0.46
7 Up Regular	3.73	3.72	3.70	3.71	3.73	-0.25	-0.63	-0.45	-0.02
7 Up Diet	1.49	1.48	1.48	1.48	1.48	-0.26	-0.67	-0.47	-0.36
Sunkist Regular	3.06	3.05	3.04	3.04	3.07	-0.28	-0.72	-0.50	0.36
Diet Rite Pure Zero Diet	0.23	0.23	0.23	0.23	0.23	-0.23	-0.58	-0.41	-0.32

Table 4: Simulated Market Shares

5   Conclusion

In this paper, we formulate a random coefficient discrete choice model of consumer demand to study the impact of consumer attention and consumer engagement on social media on CSD demand, by combing monthly CSD sales data and social media data. Consumer attention and engagement on social media is modelled as goodwill in order to capture the carry-over effects of WOM's impact on demand, following Nerlove-Arrow (1962). Our results suggest that the three types of social media messages all have significant and positive effects on CSD demand. In particular, indirect engagement on Twitter has the largest impact on consumer demand, followed by direct engagement on Twitter and consumer engagement on Facebook.

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