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Investigating the Relationship Between the Content of Online Word of Mouth, Advertising, and Brand Performance

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We study the relative importance of online word of mouth and advertising on firm performance over time since product introduction. The current research separates the *volume* of consumer-generated online word of mouth (OWOM) from its *valence*, which has three dimensions—attribute, emotion, and recommendation oriented. Firm-initiated advertising content is also classified as attribute or emotion advertising. We also shed light on the role played by advertising content on generating the different types of OWOM conversations. We use a dynamic hierarchical linear model (DHLM) for our analysis. The proposed model is compared with a dynamic linear model, vector autoregressive/system of equations model, and a generalized Bass model. Our estimation accounts for potential endogeneity in the key measures. Among the different OWOM measures, only the valence of recommendation OWOM is found to have a direct impact on sales; i.e., not all OWOM is the same. This impact increases over time. In contrast, the impact of attribute advertising and emotion advertising decreases over time. Also, consistent with prior research, we observe that rational messages (i.e., attribute-oriented advertising) wears out a bit faster than emotion-oriented advertising. Moreover, the volume of OWOM does not have a significant impact on sales. This suggests that, in our data, "what people say" is more important than "how much people say." Next, we find that recommendation OWOM valence is driven primarily by the valence of attribute OWOM when the product is new and driven by the valence of emotion OWOM when the product is more mature. Our brand-level results help us classify brands as consumer driven or firm driven, depending on the relative importance of the OWOM and advertising measures, respectively.

Keywords: dynamic hierarchical model; endogeneity; online word of mouth; attributes; emotions; recommendations; advertising
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1. Introduction

Online word of mouth (OWOM) is described as a boundless dialog with a potentially unlimited number of other Internet users (Stauss 1997). More and more, this dialog transpires in multiple forms such as text, video, and still pictures. What is remarkable about these forms of media from a business perspective is that participants frequently advocate for or against products and services as they interact. For example, according to Nielsen (2012), 46% of online users count on social media when making a purchase. A study conducted by Jack Morton (2007) reports that word of mouth was the primary influencer of buying for 53% of enterprise-level customers. According to BabyCenter (2009), 44% of moms use online consumer-generated media for product recommendations. Similarly, 53% of posters on Twitter recommend products or brands in their tweets. Furthermore, 48% of those who receive the tweets follow through on the recommendations (Gottlieb 2010).

Because these types of statistics draw attention to the power of OWOM, marketing professionals are increasingly concerned about the relative influence of OWOM versus traditional forms of marketing communications on firm performance. Worth noting is a Nielsen (2009) study that revealed 70%

of the consumers trust recommendations from other unknown online consumers more than advertisements in traditional media such as TV and radio. As it continues to proliferate and as firms are forced to make marketing resource allocation decisions, OWOM's impact versus that of traditional media will become of growing interest to marketers.

However, balancing word of mouth with traditional media is not a new challenge in the marketing communications domain, and increasingly, this challenge is expanding to OWOM. The issue of managing the influence of traditional media and word-of-mouth communications has well-established roots in the product diffusion literature (Bass 1969). Rogers (1983) argues that the theory of diffusion can be regarded as a communications theory that details how information about an innovation is transmitted via mass media (an external communication source) and interpersonal communications (an internal communication source). This literature provides a foundation for the discussion about the dynamics in marketing communication effectiveness.

2. Literature Review

2.1. Dynamics in Marketing Communication Effectiveness

The diffusion literature characterizes the dynamic effectiveness between media. According to Mahajan et al. (1995), people have different propensities for relying on mass media or interpersonal communications and that the reliance on these two communication modes changes over time. Specifically, the reliance on external communications such as TV advertisements tends to be higher initially but decreases over time. The impact of internal influences such as word of mouth (WOM) is relatively lower initially but increases and peaks around the time that the external influence is steeply declining. Internal influences also experience a decline after the peak (Horsky and Simon 1983, Rogers 1983). In the diffusion literature, it is the rise, peak, and decline of these influences that determine the speed and shape of the S-curve that typifies a product diffusion process.

Bruce et al. (2012) also address the relative effectiveness between advertising and WOM. Consistent with the diffusion literature, they estimate a dynamic linear model (DLM) using Kalman filtering to demonstrate that in categories where new products are released in sequential stages (e.g., movies are released in theaters first, and next move to the rental market or retail), traditional advertising is more effective in the early stage of the product life cycle (PLC) and word of mouth is more effective as consumers gain more experience with a product. Their explanation for these effects is traced back to the idea of advertising repetition wear-in and wearout. They argue that because advertising spending levels vary over the PLC, consumers make inferences from spending levels about product quality and firm support, which in turn lead to different levels of audience reach, interest, and desire to spread WOM. Bruce et al. explain that in the early stages of the PLC, when advertising spending is higher and growing, advertising wear-in is occurring and audience interests are higher, leading to relatively higher effectiveness of traditional advertising. However, as consumers gain experience with the product and the spending levels stabilize or possibly decrease, the effectiveness of repetition on consumers wears out, and advertising is relatively less effective when compared with WOM effects. These findings are exemplary of an emerging trend that suggests that WOM dynamically influences customer demand (Liu 2006, Moe and Trusov 2011, Trusov et al. 2009).

Another aspect of media effectiveness to consider is within-media dynamics. A consistent finding is that advertising elasticities are dynamic and decrease through the PLC (e.g., Sethuraman et al. 2011, Vakratsas and Ambler 1999). Also using a Kalman filtering procedure, Naik et al. (1998) argue that advertising effectiveness varies based on the prior exposure level at the time of the new exposure. They posit that, given prior exposure levels, repetition wearout or copy wearout can explain changes in effectiveness over time. Additionally, this wearout can occur because of changes in consumer attitudes or conditions over time (Calantone and Sawyer 1978).

A notable study that also references the wearout explanation is the work of MacInnis et al. (2002). In this research, the authors find that there are differences in wearout after repetition based on the type of advertisement. Specifically, in an experimental setting, MacInnis et al. find a positive relationship between advertising and sales for emotional ads but not rational ads. They suggest that emotional ads have a slower wearout. This finding is consistent with the experimental findings of Hitchon et al. (1988), who find that emotional ad wearout is slower when measured against attitudes toward the ad, brand attitudes, and purchase intentions. This finding was further supported by Bass et al. (2007), who estimate a DLM and confirm that emotional ads tend to have a slower copy wearout than nonemotional ads. They suggest that the slower wearout of emotional ads is related to the imagery processing (versus cognitive processing) that is prompted from these ads.

In summary, originating with the diffusion literature, research has demonstrated a dynamic relationship between traditional advertising and WOM. Extending this thinking, the literature has also documented within-media dynamics and related this back to consumer experience levels, wear-in, and wearout phenomena. Dynamic linear models and Kalman filtering have been used to capture marketing communication (MARCOM) dynamics.

2.2. OWOM and Firm Performance

Developed separately from the diffusion literature, OWOM research has begun to address the linkage between online word of mouth and firm performance. These studies have focused on descriptive variables such as the amount or volume of OWOM, the valence of the buzz,[1] and the degree of dispersion of the posts across different online forums. These descriptors are then typically linked to firm performance measures such as sales (Duan et al. 2008, Liu 2006), media ratings (Godes and Mayzlin 2004), sales rankings (Chevalier and Mayzlin 2006), stock returns (Luo 2007), or stock prices and cash flows (Luo 2009). OWOM research has also focused on the impact of positive and negative online word of mouth on firm performance (e.g., Luo 2007, Shin et al. 2008). A notable shortcoming of this stream of research is that it ignores the influence of traditional media on sales.

Research that has jointly examined the performance impact of OWOM and any form of traditional media is limited. One exception is the work by Villanueva et al. (2008), who investigate marketing (e.g., broadcast media, direct mail) versus WOM communication and use a vector autoregressive (VAR) model to examine how customers acquired using these two forms of communication affect the growth of the firm's customer equity. They find that customers acquired through marketing are more valuable in the short term, whereas customers acquired through WOM have more long-term value.

Onishi and Manchanda (2012) use a system-of-equations approach to study the impact of blogging activity and advertising on market outcomes in the movie and cellular phone industries. They find that TV advertising and blogs have a positive synergistic effect and are predictive of the magnitude of product sales and the volume of blogs. They specifically find that the synergies between blogs and TV advertising have a stronger impact on performance than the isolated effects of TV alone.

VAR or system-of-equations approaches are the typical methodologies that have been applied to study traditional versus OWOM communication effects (e.g., Duan et al. 2008, Onishi and Manchanda 2012). However, because this research stream has evolved separately from the product diffusion research, these methods overlook a substantive insight that is at the foundation of the diffusion process—specifically, these methods do not account for the *dynamic* effectiveness of traditional external media and OWOM. For example, the VAR modeling approach of Villanueva et al. (2008) assesses the short-term versus long-term impact of marketing communications experienced at one point in time (i.e., at acquisition), but the method does not account for how continued marketing communications have an evolving differential impact at different points in time. A different methodology is required to investigate the dynamics in marketing communications.

2.3. Research Contributions

In this research we build on the dynamic hierarchical linear modeling (DHLM) framework used by marketing researchers in other contexts. For example, Neelamegham and Chintagunta (2004) use a DHLM model to study how product attributes influence unit sales and prices. Researchers have also used variants of this methodology to address marketing mix problems (e.g., Ataman et al. 2010, Van Heerde et al. 2004).

Applying the DHLM model to the OWOM context enables us to extend this literature in two distinct ways. The first contribution stems from our modeling approach. We acknowledge that the VAR/system of equations approach has some benefits for studying this topic, particularly with respect to the interaction or cross effect of communication variables on firm performance and with respect to the long-term cumulative effects of an unexpected shock in one of these variables on performance. However, the multivariate dynamic hierarchical model structure allows us to investigate the evolving *dynamic* impact of communications on firm performance while also accounting for multiple endogenous regressors. The DLM (i.e., a dynamic linear model without the hierarchical component) also has these properties but does not allow for sharing of information across brands, which is relevant in our OWOM context, where we have competing products at similar stages in their product life cycle.

Unlike the VAR/system of equations approach, our dynamic modeling framework provides us with insights at different stages of the product life cycle. In addition, the proposed approach also allows for both brand-specific and aggregate-level dynamic parameter estimates. This degree of specificity could be very relevant for firms with a single product as well as for firms that manage a portfolio of products in a category. For detailed comparisons between these different models, see Van Heerde et al. (2004) and West and Harrison (1997).

The second contribution to the extant OWOM literature (e.g., Godes and Mayzlin 2004, Onishi and Manchanda 2012, Villanueva et al. 2008) and the vast

[1] Online conversations.

Figure 1 **Advertisement A: Attribute Focused**

Source: Motorola Mobility.

Figure 2 **Advertisement B: Emotion Focused**

Source: Motorola Mobility.

diffusion literature (see Mahajan et al. 1995 for a review) is the depth of the substantive investigation with respect to the *content* of both advertising and OWOM measures. Specifically, unlike prior research in these domains, we categorize the advertisements as either product attribute-oriented persuasive messages or emotion-oriented persuasive messages. The relevance of this distinction reflects the common advertising practice of delineating between rational appeals that tend to highlight attributes and emotional appeals that aim at evoking a customer–brand connection. Consider the two print ads for Motorola Razr in Figures 1 and 2.

Advertisement A (Figure 1) is "attribute" focused, whereas Advertisement B (Figure 2) is more "emotion" focused because it does not explicitly provide any information about the cell phone features or characteristics. Consistent with what we see in practice, prior researchers in the advertising domain have studied cognitive- and affective-oriented advertising content (e.g., Carpenter et al. 1994, Kardes 2005).

Similarly, we also differentiate among the types of OWOM content that are examined because not all OWOM are the same. As an illustration, consider the following online posts about the Motorola Razr phone:[2]

Post A: The *sound quality* of my Moto Razr is awesome!
Post B: I just *love* my Razr.
Post C: I would definitely *recommend* a Motorola Razr.

Although all of the above posts express a positive valence toward the focal product (i.e., Motorola Razr), their orientations are different. Post A focuses on an *attribute feature* (sound quality) of the phone, whereas post B focuses on the *emotional attachment* (love) between the poster and the phone. Post C focuses on whether the poster would *recommend* the phone to other forum users, which is expressed using the keyword "recommend." Differentiating between the *valence* of *attribute-focused OWOM*, which reflects rational processing, and the *valence* of *emotion-focused OWOM*, which reflects emotional processing, is grounded in the information processing domain of marketing research (see, for example, Cohen et al. 2008, Greifeneder et al. 2011, Shiv and Fedorikhin 1999). Acknowledging these word-of-mouth differences, we present three distinct forms of OWOM valence—namely, attribute focused, emotion focused, and recommendation focused. Prior research in the OWOM domain has not made this distinction.

Overall, our research builds on the substantive insights established by the diffusion literature and adds to the growing OWOM literature by (1) investigating which components of OWOM impact firm performance, (2) understanding the role played by advertising content on generating OWOM conversations, and (3) classifying brands as *consumer driven* and *firm driven* based on the relative importance of OWOM versus advertising. The rest of the paper is organized as follows. The next section describes the data. We then present the dynamic model used for the analysis. This is followed by a discussion of the results. We conclude the paper by highlighting the managerial implications, limitations of the research, and suggestions for future research.

3. Data Description

The product category we study in this research is cellular phones. We limit our focus to five specific brand models from the five leading cell phone companies in the United States at the time of the data. The five brand models were direct competitors with each other

[2] *Source*: Howard Forums (http://www.howardforums.com), last accessed 2007.

and new in the market at the beginning of our analysis horizon (i.e., we have data on these products from the time they were introduced into the market till they reached the mature stage of their life cycles). An example of the kind of cell phone studied would be the Motorola Razr.

3.1. OWOM Measures

Our OWOM data are from Howard Forums (http://www.howardforums.com), one of the largest cellular phone forums on the Web. The data were collected by a management consulting firm using proprietary software.[3] Independent human coders then classified the data into different online WOM categories. The firm and its software have been featured by leading marketing research firms such as Forrester Research (http://www.forrester.com). The conversations were tracked for five major cell phone brands over a two-year period from the beginning of 2005 till the end of 2006.

From the OWOM conversations, both OWOM volume and OWOM valence (attribute oriented, emotion oriented, and recommendation oriented) measures were developed using keywords. Some of these keywords are specific to the product (e.g., sleek design) and others are not (e.g., fast). The keywords used in this research were determined by matching words used in online postings with a product-specific dictionary developed in the software. The dictionary was built based on high-frequency, category-specific words used by online users in cell phone forums.

The only role of the software was to get the list and count of keywords from each of the online postings for each product. Given the list and organization of keywords, we used human coders to establish the valence of these keywords. Past academic research on OWOM categorized words as positive or negative.[4] To provide a deeper understanding of OWOM, we selected three independent coders who classified the keywords into one of four valence cells—highly negative, negative, positive, and highly positive. The coders were only told that the words referred to cellular phone characteristics or the consumer's use of cellular phones.

After the coders classified the keywords, the software counted the number of times the keywords fell into the different valence levels for each of the three OWOM categories for each online post.[5] The software allows modifications to a root word. For example, "hate" and "hated" are treated similarly. The first category is *attribute*, which means that the word relates to the product attributes and performance features of the cellphone (e.g., sound quality). The second category is *emotion*, which contains words expressing the emotions associated with the cell phone usage or ownership experience (e.g., love, hate). It is important to note that words associated with an attribute or expressing an emotion could be similar. However, the software makes the distinction as to whether the word is referencing a product attribute or an emotion associated with the product by looking for the word or phrase the keyword is modifying and then assigning the keyword to the appropriate attribute or emotion category.

For example, consider the following two sentences: (1) The Motorola Razr is an *annoying* phone. (2) The voice quality of Motorola Razr is *annoying*. The software would classify "annoying" in the first sentence as an emotion keyword, whereas the word "annoying" in the second sentence would be classified as an attribute keyword because of the attribute-related phrase ("voice quality") it is modifying. Therefore, we can have similar keywords classified as attribute or emotion specific depending on the context.

The third classification category of keywords is *recommendation*-related keywords. These words capture whether the customer recommends or is an advocate of the phone to others or not (e.g., "recommend," "buy," "purchase").

Based on the valence classification of the keywords by the independent coders, we have the following three valence measures—*ATTRIBUTE OWOM VALENCE*, *EMOTION OWOM VALENCE*, and *RECOMMENDATION OWOM VALENCE* for each post. These measures are then aggregated to the brand–month level. To arrive at each valence measure, we compute a weighted average valence for each brand in each month using a -2 to $+2$ scale, where a weight of -2 was given to the highly negative words, -1 for negative words, $+1$ for positive words, and $+2$ for highly positive words. In addition to the valence measures for each brand, we also measure the absolute volume of brand-specific posts at time t and refer to this as *OWOM VOLUME*. Thus, our OWOM measures go beyond the typical measures of valence and volume of the conversations. Instead, each of our valence measures take into account the nature of conversations (attribute, emotion, or recommendation oriented).

3.2. Sales, Advertising, and Price Measures

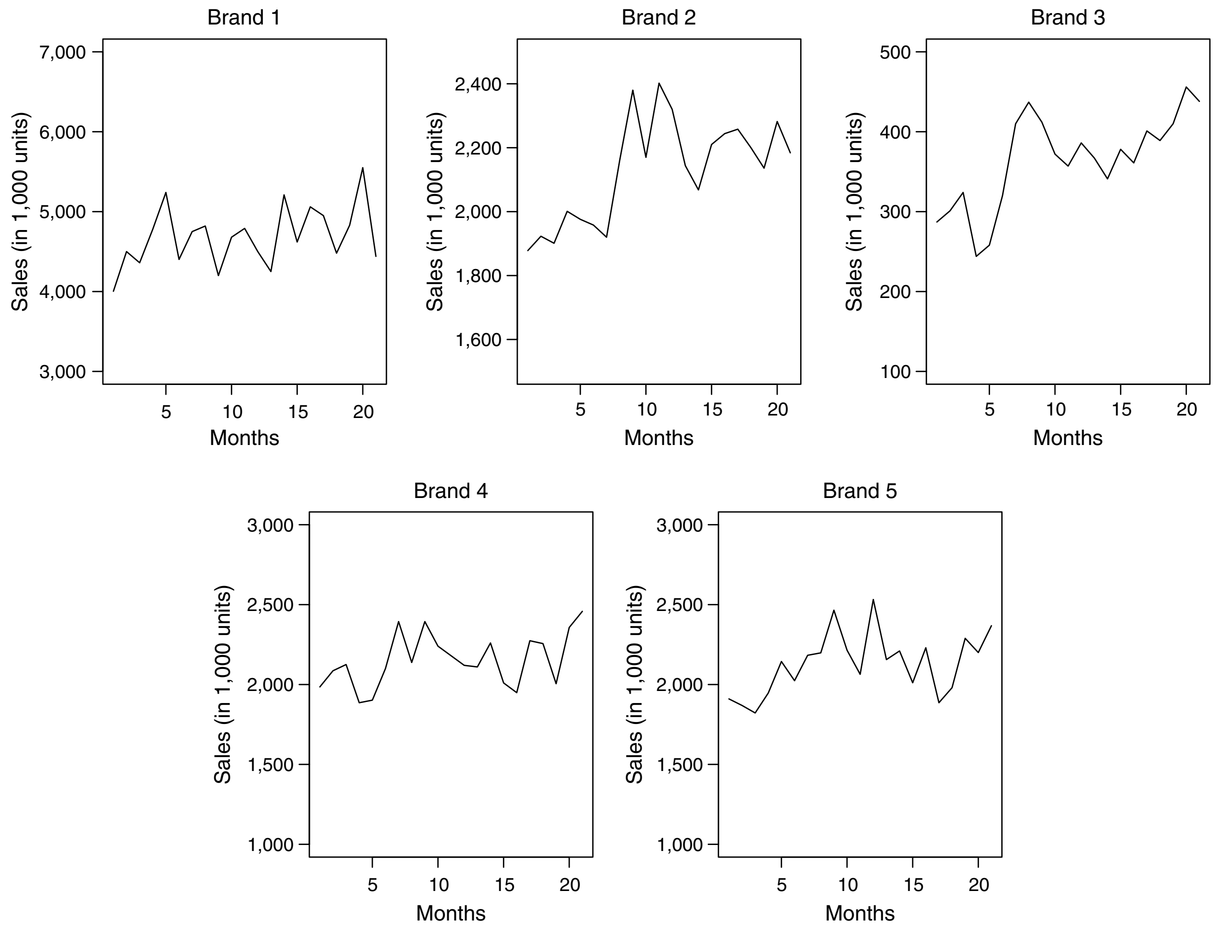
We supplement the OWOM data with monthly sales, price, and advertising data for each brand model. The sales patterns for the five brands are shown in Figure 3. The sales data are the unit sales for each brand

[3] Because of nondisclosure agreements, we cannot reveal the name of the firm.

[4] A notable exception is Godes and Mayzlin (2004), who classify posts as positive, negative, and neutral for 10% of their sample.

[5] The software correctly classifies a negative phrase with a seemingly positive word (e.g., "do not love"), and vice versa.

Figure 3 **Sales Dynamics for Leading Cell Phone Brand Models**



model,[6] and the advertising data are the number of advertisements for each brand model via all the major channels—TV, cinema, print, billboards, and radio. However, almost 90% of the advertisements in our data are in the TV and print category. Because one of our key objectives is to investigate the role of the content of advertising on sales and OWOM generation, the advertisements were classified by independent human coders as "attribute" focused or "emotion" focused.[7] The reliability scores are mentioned in the section below. Once all the advertisements were classified, we used the following two measures for the content of advertising: *ATTRIBUTE ADV* and *EMOTION ADV*.[8] These measures capture the number of advertisements that are "attribute" focused and "emotion" focused, respectively, for each brand model in each month. Similar to prior OWOM research using advertising measures (e.g., Onishi and Manchanda 2012), we do not have exposure data for each channel in the cell phone category. Hence, we assume equal exposure to the different channels. However, we test the robustness of our results by varying the exposure levels of the two major channels (TV and print). The statistical significance of the effects, order of magnitude of the parameters, and the trends over time are the same as those obtained under the equal exposure assumption. Hence, in the rest of the paper, we will focus on the results obtained with the equal exposure assumption.

3.3. Competition Variables

In addition to our focal variables, we also included four variables to control for competitive effects. The first variable is *COMP_OWOM VOLUME*, which is the volume of buzz generated by competing products. The second competition variable is *COMP_OWOM VALENCE*, which is the average valence of buzz generated by competing products. The competition measures incorporate all brands and all types of OWOM conversations (recommendation oriented, attribute oriented, and emotion oriented). This helps us capture the overall competition sentiment while keeping the

[6] Although the unit of analysis is a brand model (e.g., Motorola Razr), we use "brand" and "brand model" interchangeably throughout the paper.

[7] No software package was used to classify the firm advertising as "attribute" or "emotion" focused.

[8] Firm advertisements are persuasive in nature and hence are by definition positive in their impact.

Table 1 Descriptive Statistics

Variable	Description	Min	Max	Mean	SD
$SALES_{bt}$ (in 1,000 units)	Sales for cell phone brand model (e.g., Motorola Razr) b in time t	258.00	5,611.00	2,322.00	1,449.00
$PRICE_{bt}$ (in dollars)	Price for cell phone brand b in time t	12.25	350.20	124.00	75.96
$RECOMMENDATION\ OWOM\ VALENCE_{bt}$	Valence of recommendation-related OWOM conversations regarding brand b in time t	−0.02	0.61	0.14	0.12
$ATTRIBUTE\ OWOM\ VALENCE_{bt}$	Valence of attribute-related OWOM conversations regarding brand b in time t	−0.05	1.13	0.36	0.24
$EMOTION\ OWOM\ VALENCE_{bt}$	Valence of emotion-related OWOM conversations regarding brand b in time t	−0.03	0.52	0.18	0.14
$OWOM\ VOLUME_{bt}$	Volume of OWOM conversations regarding brand b in time t	9,534	32,150	16,830	5,588.39
$ATTRIBUTE\ ADV_{bt}$	Number of attribute-focused advertisements regarding brand b in time t	3.00	23.00	10.46	6.23
$EMOTION\ ADV_{bt}$	Number of emotion-focused advertisements regarding brand b in time t	5.00	27.00	8.75	5.82
$COMP\_OWOM\ VOLUME_t$	Total volume of OWOM conversations about competing brands in time t	13,286	78,495	31,524	6,128.47
$COMP\_OWOM\ VALENCE_t$	Average valence of OWOM conversations about competing brands in time t	−0.06	1.08	0.21	0.19
$COMP\_ADVERTISING_t$	Total number of advertisements for competing brands in time t	19.00	128.00	42.41	12.36
$COMP\_PRICE_t$	Average price of competing brands in time t	11.00	384.25	136.80	84.12

model specification parsimonious. The third competition variable is *COMP_ADVERTISING*, which is the total number of advertisements for competing products. We expect a higher value for these three OWOM-based competition variables to lower own-product sales. The final competition variable is *COMP_PRICE*, which is the average price of competing products. We expect a positive relationship between this variable and sales.

3.4. Coder Reliability of OWOM and Advertising Measures

For the measures that were determined by human coders, different measures of reliability are calculated. Although Nunnally (1978) suggests a minimum reliability of 0.7, other methodologists (e.g., Frey et al. 2000, Krippendorff 1980) have suggested reliability values of 0.8 or greater. Because we have ordinal variables, we use Krippendorff's R and Krippendorff's r bar, which are the ordinal versions of Cohen's kappa and Scott's pi agreement measures. The reliability numbers for both the OWOM and advertising measures are all greater than 0.7; most of them are greater than 0.8, and some are greater than 0.9. This implies that there is a reasonably high level of consistency in the keyword classifications of the three independent coders.[9]

Table 1 provides the definitions and summary statistics of the key variables used in the analysis.

[9] We never had instances where all three coders disagreed on the classification. However, in cases where one coder differed, we classified the word according to the two consistent coders.

4. Methodology

4.1. Overview

We model how brand sales are influenced by the content of OWOM and firm advertising using a DHLM. A similar modeling approach has been used by prior researchers in the marketing and statistics literature (e.g., Landim and Gamerman 2000, Neelamegham and Chintagunta 2004) to capture time-varying relationships. DLMs, which use a similar framework, have been used more extensively (e.g., Ataman et al. 2010). The key difference between the DLM and the DHLM is the hierarchical structure in the DHLM, which allows us to pool information across the different brands to arrive at overall aggregate-level inferences. This shrinking of the brand-level parameters to an "average" effect of the key measures across brands is made possible because of the panel nature of the data. This approach has been used by other researchers as well (e.g., Montgomery 1997, Montgomery and Rossi 1999, Neelamegham and Chintagunta 2004).

A typical DHLM specification consists of three equations—observation equation, pooling equation, and evolution equation. The *observation equation* captures the dependent measure of interest specified as a function of the explanatory variables and time-varying parameters. Note that the time-varying parameters in the observation equation are *brand specific*. The *pooling equation* specifies the relationship among these time-varying brand-level parameters and a new set of parameters that vary *only in time*. This hierarchical structure pools information across brands for each point in time. We are able to pool the brand parameters since the brand models were all in the same stage of the product life cycle; i.e., the parameters are assumed to be exchangeable (see Landim and Gamerman 2000 for details on exchangeability). The advantage of this structure is the ability to estimate the effect of the variables for each brand over time as well an overall category effect over time. Finally, the *evolution equation* specifies the time evolution of the parameters. This equation captures the effects of the content of OWOM and advertising over the product life cycle.

To account for any endogeneity, we include each of the OWOM measures, advertising measures, and price as dependent variables in the model. Moreover, we also account for own-performance feedback (via effects of lagged sales) and inertia (via effects of lagged dependent variables).[10]

The mathematical specification of our dynamic model is presented below:

Observation equation:

$$y_{bt} = F_{bt}\beta_{bt} + v_{bt}, \quad v_{bt} \sim \mathrm{N}(0, V_1), \tag{1}$$

Pooling equation:

$$\beta_{bt} = D\theta_t + \upsilon_{bt}, \quad \upsilon_{bt} \sim \mathrm{N}(0, V_2), \tag{2}$$

Evolution equation:

$$\theta_t = G\theta_{t-1} + \omega_t, \quad \omega_t \sim \mathrm{N}(0, W). \tag{3}$$

Here, y_{bt} is a multivariate vector and includes $SALES_{bt}$, as well as the four OWOM measures ($RECOMMENDATION\ OWOM\ VALENCE_{bt}$, $ATTRIBUTE\ OWOM\ VALENCE_{bt}$, $EMOTION\ OWOM\ VALENCE_{bt}$, and $OWOM\ VOLUME_{bt}$), the two advertising content measures ($ATTRIBUTE\ ADV_{bt}$ and $EMOTION\ ADV_{bt}$), and price ($PRICE_{bt}$); F_{bt} includes the covariates for brand b at time period t, consisting of the four lagged OWOM measures ($RECOMMENDATION\ OWOM\ VALENCE_{b,t-1}$, $ATTRIBUTE\ OWOM\ VALENCE_{b,t-1}$, $EMOTION\ OWOM\ VALENCE_{b,t-1}$, and $OWOM\ VOLUME_{b,t-1}$), the two lagged firm-initiated advertising measures ($ATTRIBUTE\ ADV_{b,t-1}$ and $EMOTION\ ADV_{b,t-1}$), and key interactions between OWOM and advertising. In the model we also control for time-varying brand fixed effects, own-performance feedback ($SALES_{b,t-1}$), price ($PRICE_{bt}$), and competition variables. Note that the key covariates are lagged by one period, as is typical in the OWOM research (e.g., Chintagunta et al. 2010, Godes and Mayzlin 2004, Liu 2006)[11] and is consistent with the carryover effect of advertising (e.g., Bass and Leone 1983, Clarke 1976). We use standardized variables of the key measures to facilitate direct comparison of the estimates: β_{bt} is the vector of brand-specific coefficients at time t, which are obtained by utilizing the brand-level variation in the covariates contained in F_{bt}; θ_t is the vector of the time-specific mean value of the brand-level coefficients (β_{bt}); D is a matrix of zeros and ones to adjust the size of θ_t to that of β_{bt}; and G is an identity matrix.

The interaction terms could also be potentially endogenous, but specifying a generation process would be difficult, and this is a limitation. However, we have accounted for endogeneity in the main effects that are used to create the interactions. Hence, any endogeneity effects as a result of the interaction terms are likely to be minimal.

4.2. Estimation

The dynamic hierarchical linear model is estimated in a hierarchical Bayes framework building on the algorithm proposed by West and Harrison (1997). Specifically, we estimate Equations (1)–(3) jointly, and we allow the error terms to be correlated. This enables us to account for common unobserved shocks that may jointly influence cell phone sales, price, advertising content, and the generation of OWOM content. Other researchers (Ataman et al. 2010, Neelamegham and Chintagunta 2004) have used a similar estimation approach in non-OWOM contexts. The details of the estimation procedure are in the appendix.

5. Empirical Results

5.1. Model Comparisons

We compare our model with three other benchmark models—namely, a dynamic linear model, a VAR model, and a generalized Bass model. The specifications of the models are as follows.

5.1.1. Dynamic Linear Model. The dynamic linear model (DLM) is specified as follows:

$$Y_{bt} = X_{bt}\lambda_{bt} + \zeta_{bt}, \quad \zeta_{bt} \sim \mathrm{N}(0, V_\zeta), \tag{4}$$

$$\lambda_{bt} = \lambda_{b,t-1} + \nu_{bt}, \quad \nu_{bt} \sim \mathrm{N}(0, V_\nu). \tag{5}$$

The above specification allows for time-varying parameters for each of the independent variables. The dependent variables (Y_{bt}) and independent variables (X_{bt}) are the same as those in the proposed model. Moreover, Equation (5) is similar to the evolution equation (Equation (3)) of the proposed DHLM. The

[10] We also examined cross-performance feedback, contemporaneous measures, and seasonality variables. However, they were not found to be significant and hence were removed from the final specification.

[11] Moreover, the model with single-period lag fits best based on Akaike information criterion and Schwarz criterion (Campbell and Mankiw 1987).

DLM, similar to the DHLM, accounts for endogeneity. However, the model does not have a pooling equation and hence does not allow for information sharing across brands, which is the key difference between this model and the proposed model.

5.1.2. VAR Model. The VAR model has a similar specification as the observation equation (Equation (1)) of our proposed DHLM model. The first key difference is that the parameters are not time varying. In addition, the VAR model does not have the pooling and evolution equations:

$$Y_{bt} = \Phi Y_{b,\,t-1} + E_{bt}, \quad E_{bt} \sim \mathrm{N}(0, \Sigma), \tag{6}$$

Here, Y_{bt} is the same vector of dependent variables as in (1), and Φ captures the relevant coefficients.

5.1.3. Generalized Bass Model. A standard model used in the product diffusion literature is the Bass model, which typically does not include covariates. For appropriate comparison to our proposed model, we estimate a generalized Bass model (Bass et al. 1994) that allows for covariates. The model is specified as follows:

$$\begin{aligned} &SALES_{bt} \\ &= \left[p_b m_b + (q_b - p_b) CUMSALES_{bt} - \frac{q_b}{m_b}(CUMSALES_{bt})^2\right] \\ &\quad \times [1 + \delta_{1b} PROWOM_{bt} + \delta_{2b} PAOWOM_{bt} \\ &\qquad + \delta_{3b} PEOWOM_{bt} + \delta_{4b} POWOMVOL_{bt} \\ &\qquad + \delta_{5b} PAADV_{bt} + \delta_{6b} PEADV_{bt} + \Gamma Z], \end{aligned} \tag{7}$$

where $SALES_{bt}$ is the sales of brand b in time t and $CUMSALES_{bt}$ is the cumulative sales of brand b up to time t. $PROWOM_{bt}$, $PAOWOM_{bt}$, $PEOWOM_{bt}$, $POWOMVOL_{bt}$, $PAADV_{bt}$, and $PEADV_{bt}$ are the percentage changes (from the previous time period) in recommendation OWOM valence, attribute OWOM valence, emotion OWOM valence, OWOM volume, attribute advertising, and emotion advertising for brand b at time t. The matrix Z includes the percentage changes for the interactions between OWOM and advertising and OWOM and the control variables (competition variables and price). The coefficients associated with these covariates are $(\delta 1_b, \ldots, \delta 6_b, \Gamma)$, (p_b, q_b) are the coefficients of innovation and imitation for brand b, and m_b is the market potential for brand b. Although the above model provides brand-level results, we only obtain time-invariant substantive insights regarding the product diffusion process.

5.1.4. Comparing Model Fits. The model comparisons (see Table 2) are made using the mean absolute percentage error (MAPE), which is a standard fit statistic for model comparisons (e.g., Neelamegham and Chintagunta 2004). We find that both the DLM and the generalized Bass model (GBM) have similar fits, and the VAR model has the lowest fit. The proposed DHLM model provides better in-sample and out-of-sample fits than all the three alternative models. In addition to providing better model fit when compared with the alternative models, the proposed DHLM aids us in our key objective, which is obtaining time-varying parameter estimates both at the brand level and the category level.

Table 2 **Model Comparisons**

	Model			
	VAR	GBM	DLM	DHLM (proposed model)
Substantive insights =	Brand-level parameters	Brand-level parameters	Brand-level time-varying parameters	Brand-level and overall time-varying parameters
Time-varying parameters	No	No	Yes	Yes
Information sharing across brands	No	No	No	Yes
Account for endogenous regressors	Yes	No	Yes	Yes
Product life cycle insights	No	Yes	Yes	Yes
Log marginal likelihood	−929.88	−914.32	−909.55	−887.73
Log Bayes factor	42.15	26.59	21.82	—
In-sample fit—MAPE	7.34	6.64	6.56	4.15
Out-of-sample forecasts—MAPE (at 18 months)	18.39	16.85	16.43	9.79

In addition, we compare the predictive validity of each of the alternative models using the log Bayes factor (Ataman et al. 2008, West and Harrison 1997). A log Bayes factor greater than 2 indicates strong evidence in favor of the null model (our proposed DHLM). Table 2 shows that the proposed DHLM outperforms the three alternative models because the log Bayes factors are greater than 2. The log-marginal likelihoods are also reported for all the models.

It is important to note that Equation (1) of the DHLM accounts for possible endogeneity of all of our key regressors. Also, Equations (1)–(3) are estimated jointly. This yields unbiased estimates of the effects of key measures on sales, the four OWOM measures, the two advertising measures, and price. We now discuss the main results.

5.2. Key Drivers of Firm Performance

In this section we focus on the role played by the different OWOM measures (*RECOMMENDATION OWOM VALENCE, ATTRIBUTE OWOM VALENCE,*

Table 3 **Parameter Estimates of SALES Model—Overall (θ_t)**

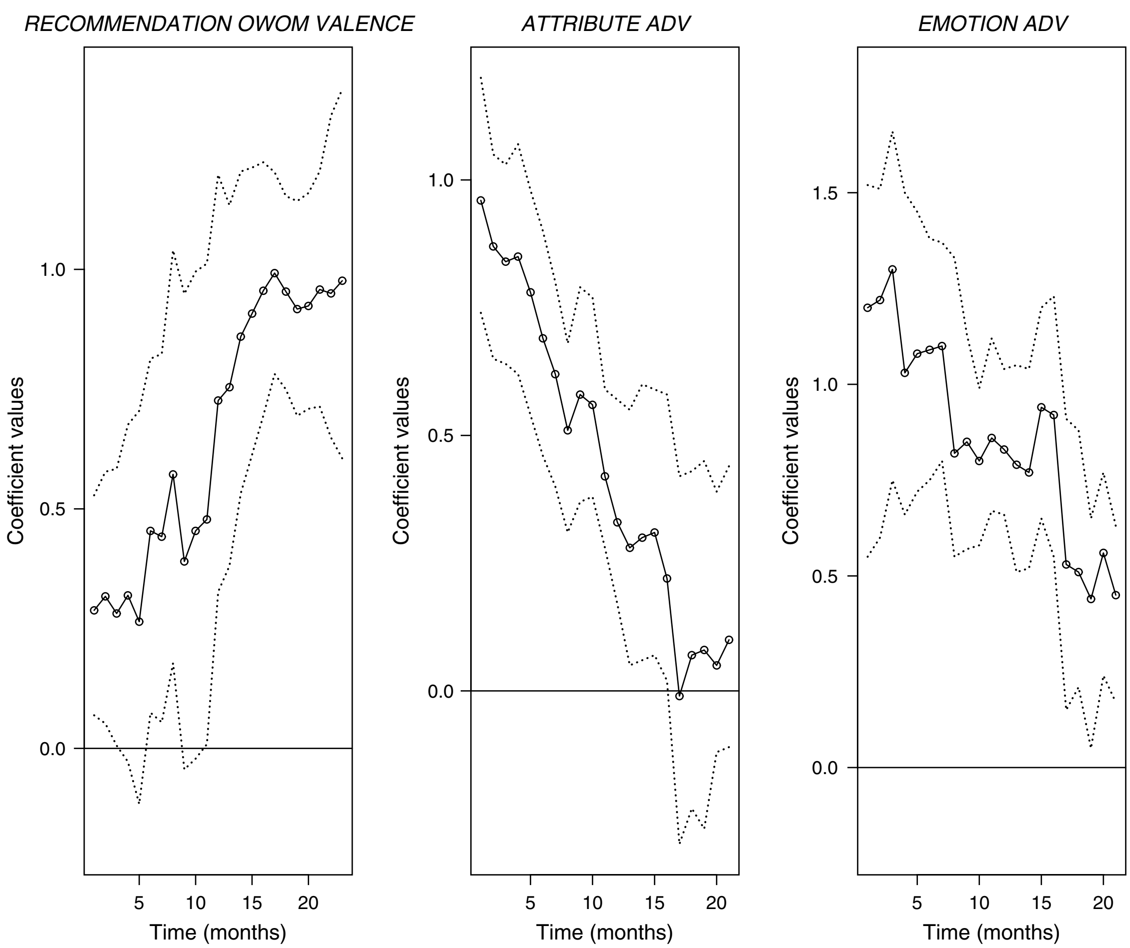
Parameter	Mean	[2.5th percentile, 97.5th percentile]
$SALES_{t-1}$	0.96*	[0.62, 1.29]
$OWOM\ VOLUME_{t-1}$	0.11	[−0.15, 0.38]
$RECOMMENDATION\ OWOM\ VALENCE_{t-1}$	0.63*	[0.31, 0.93]
$ATTRIBUTE\ OWOM\ VALENCE_{t-1}$	0.05	[−0.18, 0.24]
$EMOTION\ OWOM\ VALENCE_{t-1}$	0.18	[−0.06, 0.38]
$ATTRIBUTE\ ADV_{t-1}$	0.32*	[0.17, 0.56]
$EMOTION\ ADV_{t-1}$	0.68*	[0.42, 0.95]
$ATTRIBUTE\ OWOM\ VALENCE_{t-1} \times ATTRIBUTE\ ADV_{t-1}$	0.21*	[0.03, 0.42]
$EMOTION\ OWOM\ VALENCE_{t-1} \times EMOTION\ ADV_{t-1}$	0.34*	[0.09, 0.57]
$PRICE_t$	−0.27*	[−0.08, −0.53]
$COMP\_OWOM\ VOLUME_t$	−0.06	[−0.28, 0.14]
$COMP\_OWOM\ VALENCE_t$	−0.21*	[−0.35, −0.09]
$COMP\_ADVERTISING_t$	−0.29*	[−0.54, −0.08]
$COMP\_PRICE_t$	0.08	[−0.12, 0.31]

*The 95% confidence interval does not include zero.

EMOTION OWOM VALENCE, and *OWOM VOLUME*), advertising content (*ATTRIBUTE ADV* and *EMOTION ADV*), and their interactions in driving firm performance (*SALES*). The overall parameter estimates (θ_t) are shown in Table 3, whereas the time-varying effects of the key variables that are statistically different from zero are shown in Figure 4. Note that the variables are standardized, so the effect sizes in Table 3 are directly comparable. The solid lines in Figure 4 represent the mean time-varying effects, and the 95% confidence intervals are depicted by the dotted lines.

From Table 3, we note three key findings from this analysis. First, even after accounting for inherent differences across the brands (brand-specific fixed effects), performance feedback (lagged sales), own price, and competition variables, *RECOMMENDATION OWOM VALENCE* has a significant direct impact on future firm performance (*SALES*). Second, the other two OWOM valence components, *ATTRIBUTE OWOM VALENCE* and *EMOTION OWOM VALENCE*, do not have a direct impact on sales. Third, although both forms of advertising are important, emotion advertising (*EMOTION ADV*) has a bigger impact (on average twice the impact) than attribute advertising (*ATTRIBUTE ADV*) on next-period sales in this category.

Figure 4 **Key Drivers of Sales Over Time—Overall (θ_t)**



Notes. Solid lines represent the mean time-varying effect, whereas the 95% confidence intervals are depicted by dotted lines.

Interestingly, prior-period *OWOM VOLUME* does not have a significant impact on sales. This suggests that in our data, "what people say" is more important than "how much people say." Other researchers (e.g., Chintagunta et al. 2010, Godes and Mayzlin 2004) have also found a similar result.

Table 3 also shows that there is an interaction between emotional OWOM (*EMOTION OWOM VALENCE*) and emotion-oriented advertising (*EMOTION ADV*) and between attribute-oriented OWOM (*ATTRIBUTE OWOM VALENCE*) and attribute-oriented advertising (*ATTRIBUTE ADV*). Additionally, the interaction between *EMOTION OWOM VALENCE* and *EMOTION ADV* is stronger than that between *ATTRIBUTE OWOM VALENCE* and *ATTRIBUTE ADV*. This suggests that, overall, there is more synergy between the emotional aspects of firm-generated media and consumer-generated media.

The control variables have the expected signs. We find a positive impact of lagged sales and negative impact of own price. Both OWOM valence of competing products (*COMP_OWOM VALENCE*) and competition advertising (*COMP_ADVERTISING*) have significant negative impacts on firm performance. The coefficients of the other two competition variables (*COMP_OWOM VOLUME* and *COMP_PRICE*) are not significant.

Looking at Figure 4, we see how the effects vary over time for the key OWOM and advertising measures of interest. The coefficients are significant at a particular time point if their confidence intervals (shown by the dotted lines) do not intersect with the zero line. We find that the impact of *RECOMMENDATION OWOM VALENCE* increases as the product matures, whereas the impact of attribute-focused advertising (*ATTRIBUTE ADV*) and emotion-focused advertising (*EMOTION ADV*) decreases over time. Thus, advertising has a stronger effect than OWOM at the product introduction stage.

However, between the two advertising measures, only *EMOTION ADV* has a positive and significant impact when the product has reached a mature stage. These findings are consistent with findings from the literature that compares the dynamic effectiveness of advertising and WOM (e.g., Mahajan et al. 1995) and the advertising research literature that suggests that emotion advertising wears out more slowly than rational advertising (e.g., MacInnis et al. 2002).

5.3. Key Drivers of Recommendation OWOM Valence

We first focus on the results from the RECOMMENDATION OWOM VALENCE model since we found from the earlier results (see Table 3) that only the recommendation-related online conversations have a direct impact on sales.

Table 4 Parameter Estimates of RECOMMENDATION OWOM VALENCE and OWOM VOLUME Models—Overall (θ_t)

Parameter	Mean	[2.5th percentile, 97.5th percentile]
RECOMMENDATION OWOM VALENCE model		
$ATTRIBUTE\ OWOM_{t-1}$	0.62*	[0.35, 0.91]
$EMOTION\ OWOM_{t-1}$	0.91*	[0.58, 1.27]
$RECOMMENDATION\ OWOM_{t-1}$	0.54*	[0.33, 0.78]
$ATTRIBUTE\ ADV_{t-1}$	0.11	[−0.14, 0.43]
$EMOTION\ ADV_{t-1}$	0.26*	[0.08, 0.52]
$ATTRIBUTE\ OWOM\ VALENCE_{t-1} \times ATTRIBUTE\ ADV_{t-1}$	0.01	[−0.18, 0.21]
$EMOTION\ OWOM\ VALENCE_{t-1} \times EMOTION\ ADV_{t-1}$	0.17*	[0.04, 0.32]
$OWOM\ VOLUME_{t-1}$	0.06	[−0.15, 0.28]
$SALES_{t-1}$	0.12	[−0.11, 0.39]
OWOM VOLUME model		
$ATTRIBUTE\ OWOM_{t-1}$	0.15*	[0.03, 0.29]
$EMOTION\ OWOM_{t-1}$	0.04	[−0.18, 0.20]
$RECOMMENDATION\ OWOM_{t-1}$	0.09	[−0.11, 0.27]
$ATTRIBUTE\ ADV_{t-1}$	0.37*	[0.15, 0.62]
$EMOTION\ ADV_{t-1}$	0.19*	[0.06, 0.35]
$ATTRIBUTE\ OWOM\ VALENCE_{t-1} \times ATTRIBUTE\ ADV_{t-1}$	0.26*	[0.10, 0.44]
$EMOTION\ OWOM\ VALENCE_{t-1} \times EMOTION\ ADV_{t-1}$	0.03	[−0.19, 0.23]
$OWOM\ VOLUME_{t-1}$	0.40*	[0.16, 0.68]
$SALES_{t-1}$	0.18*	[0.05, 0.34]

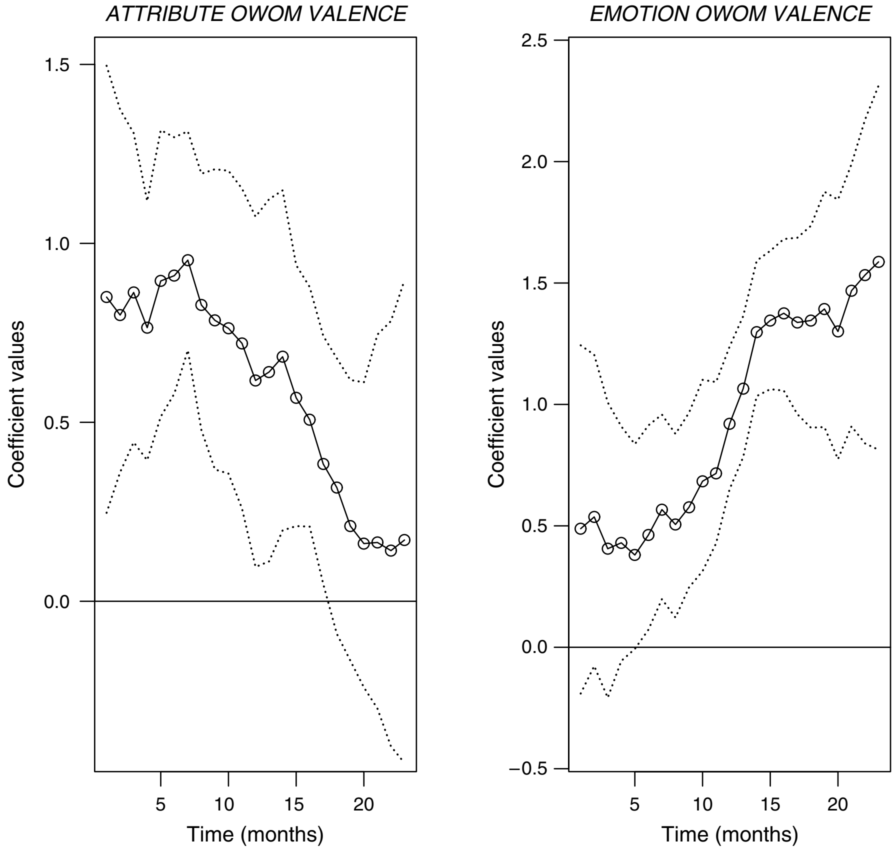
*The 95% confidence interval does not include zero.

From Table 4, we find that the valence of *attribute- and emotion*-related OWOM conversations (*ATTRIBUTE OWOM VALENCE* and *EMOTION OWOM VALENCE*) have a positive and significant impact on online customer recommendations (*RECOMMENDATION OWOM VALENCE*). Interestingly, prior-period *OWOM VOLUME* and prior-period sales did not affect the valence of *RECOMMENDATION OWOM VALENCE*. This suggests that the content of OWOM matters more with respect to the formation of recommendations rather than the volume of buzz or the volume of prior sales. In other words, "popularity" is not sufficient to warrant a positive recommendation.

Between the two advertising components, emotion advertising (*EMOTION ADV*) has a significant effect, but it is smaller than the effects of the attribute and emotion OWOM components. We also find a positive and significant interaction between the valence of emotion OWOM (*EMOTION OWOM VALENCE*) and emotion advertising (*EMOTION ADV*). This suggests that only emotional ads influence recommendation OWOM conversation both directly and through interacting with OWOM emotion-related conversations.

Furthering these insights, Figure 5 shows the time-varying nature of the key parameters. We find that the valence of rational online conversations focused on product attributes/features (*ATTRIBUTE OWOM VALENCE*) initially has a positive impact on *RECOMMENDATION OWOM VALENCE*. This effect wears

Figure 5 **Key Drivers of *RECOMMENDATION OWOM VALENCE* Over Time—Overall (θ_t)**



Notes. Solid lines represent the mean time-varying effect, whereas the 95% confidence intervals are depicted by dotted lines.

out or declines over time. Interestingly, conversations related to the emotional bond between the online poster and the product (*EMOTION OWOM VALENCE*) initially have a lower positive impact than *ATTRIBUTE OWOM VALENCE*. However, the effect becomes more and more positive over time. From the 14th month onward, *EMOTION OWOM VALENCE* is the key driver of *RECOMMENDATION OWOM VALENCE*, whereas *ATTRIBUTE OWOM VALENCE* eventually wears out such that it does not have a significant positive impact. This varying importance of *ATTRIBUTE OWOM VALENCE* and *EMOTION OWOM VALENCE* depending on the stage of the product life cycle is a unique and key insight that is derived from the DHLM methodology. If we only looked at the average effects (Table 4), we would simply have inferred that *EMOTION OWOM VALENCE* is more important than *ATTRIBUTE OWOM VALENCE* and missed this more complex relationship.

Thus, by using the DHLM methodology, a firm can determine directionally what *type* of consumer information processing (i.e., attribute oriented versus emotion oriented) is associated with higher levels of customer recommendation for the product (*RECOMMENDATION OWOM VALENCE*) at different points in a product's life cycle. Because *RECOMMENDATION OWOM VALENCE* directly affects sales, it is important to know how to drive recommendations throughout the product life cycle.

5.4. Impact of Advertising Content on Attribute and Emotion OWOM Generation

To complete our media perspective, we also look at the role played by advertising content on influencing the attribute and emotion components of OWOM valence. Table 5 and Figure 6 show the overall estimates (θ_t) for the ATTRIBUTE OWOM VALENCE and EMOTION OWOM VALENCE models.

From Table 5, the key result is that *ATTRIBUTE ADV* affects both attribute-related OWOM (*ATTRIBUTE OWOM VALENCE*) and emotion-related OWOM (*EMOTION OWOM VALENCE*). However, *EMOTION ADV* affects only emotion-related OWOM (*EMOTION OWOM VALENCE*). This makes intuitive sense, because emotion-focused advertising does not contain any information regarding product attributes to facilitate attribute-related discussions in the online forums. Moreover, the interaction between attribute OWOM and attribute advertising is significant for both attribute and emotion OWOM models, whereas

Table 5 Parameter Estimates of ATTRIBUTE and EMOTION OWOM VALENCE Models—Overall (θ_t)

Parameter	Mean	[2.5th percentile, 97.5th percentile]
ATTRIBUTE OWOM VALENCE model		
$ATTRIBUTE\ OWOM_{t-1}$	0.59*	[0.35, 0.82]
$EMOTION\ OWOM_{t-1}$	0.23*	[0.09, 0.41]
$RECOMMENDATION\ OWOM_{t-1}$	0.10	[−0.16, 0.37]
$ATTRIBUTE\ ADV_{t-1}$	0.78*	[0.49, 1.10]
$EMOTION\ ADV_{t-1}$	0.08	[−0.16, 0.35]
$ATTRIBUTE\ OWOM\ VALENCE_{t-1} \times ATTRIBUTE\ ADV_{t-1}$	0.31*	[0.14, 0.51]
$EMOTION\ OWOM\ VALENCE_{t-1} \times EMOTION\ ADV_{t-1}$	0.02	[−0.17, 0.22]
$OWOM\ VOLUME_{t-1}$	0.07	[−0.15, 0.29]
$SALES_{t-1}$	0.10	[−0.14, 0.32]
EMOTION OWOM VALENCE model		
$ATTRIBUTE\ OWOM_{t-1}$	0.29*	[0.12, 0.49]
$EMOTION\ OWOM_{t-1}$	0.48*	[0.27, 0.68]
$RECOMMENDATION\ OWOM_{t-1}$	0.11	[−0.15, 0.36]
$ATTRIBUTE\ ADV_{t-1}$	0.34*	[0.14, 0.51]
$EMOTION\ ADV_{t-1}$	0.71*	[0.41, 1.04]
$ATTRIBUTE\ OWOM\ VALENCE_{t-1} \times ATTRIBUTE\ ADV_{t-1}$	0.22*	[0.07, 0.38]
$EMOTION\ OWOM\ VALENCE_{t-1} \times EMOTION\ ADV_{t-1}$	0.43*	[0.18, 0.71]
$OWOM\ VOLUME_{t-1}$	0.11	[−0.06, 0.30]
$SALES_{t-1}$	0.09	[−0.08, 0.27]

*The 95% confidence interval does not include zero.

the interaction between emotion OWOM and emotion advertising is significant only for the emotion OWOM model.

Figure 6 gives us the following additional insights. *ATTRIBUTE ADV* has a very big impact on valence of *ATTRIBUTE OWOM* when the product has just been introduced into the market. However, this high impact level declines rapidly as the product starts to mature. On the other hand, *EMOTION ADV* has a more consistent or stable impact on the valence of *EMOTION OWOM*.

5.5. Brand-Level Results

The DHLM methodology allows us to derive brand-level results via parameters that are both brand- and time-varying (β_{bt}). Overall, the brand-level results (see Table 6) are qualitatively similar to the overall results described earlier; i.e., sales are primarily driven by the two components of advertising (attribute and emotion) and the valence of recommendation component of OWOM. Moreover, the evolution of the effects of the OWOM and advertising measures are similar to the overall effects (see Figure 4) and hence are omitted for brevity. However, we do find brand-level differences for some of the other OWOM effects. For brand 2 we find that the volume of OWOM and valence of attribute OWOM conversations have a significant impact on sales. In contrast, for brands 1 and 5, it is the valence of emotion OWOM component that has a significant effect on sales.

In addition, we find that sales are driven more by the consumer-generated measure (*RECOMMENDATION OWOM VALENCE*) for brands 1 and 2 than for the other brands. Interestingly, brand 3 is more influenced by firm-initiated advertising (*ATTRIBUTE ADV* and *EMOTION ADV*) compared with the other brands. Brand 4 is also more influenced by advertising but only emotion-oriented advertising specifically. The influence of attribute-oriented advertising and OWOM recommendations is similar. These brand-level insights help marketers classify brands 1 and 2 as *consumer-driven brands*, brand 3 as a *firm-driven brand*, and brand 4 *as more firm driven but not as much as brand* 3. The analysis also suggests that brand 5 is the most *balanced* with respect to the firm versus consumer influence. Thus, from a brand management perspective, these types of insights suggest that different tactics may be more appropriate and successful with some brands versus others. For example, grassroots marketing or the establishment of brand advocacy groups may be tactics that suit the consumer-driven brands well.

5.6. Long-Term Impacts of Advertising and Online WOM

In this section we use our proposed DHLM to assess the long-term impacts of the different advertising and OWOM measures. For each of the key measures, we calculate the percentage change in forecasted sales due to a 1% increase in the focal measure. Specifically, we calculate the cumulative implication of this shock on sales over a time window of 12 months. This time frame is consistent with prior research (e.g., Ataman et al. 2008, Leone 1995).

Table 7 shows the results of this analysis. The first key finding is that recommendation OWOM valence and emotion advertising have the biggest long-term impact. The second key finding is that the OWOM volume and valences of the attribute and emotion components of OWOM have positive long-term impacts in contrast to their lack of significance when short-term impacts are considered (see Table 3). This result suggests stronger indirect impacts of these OWOM components on sales.

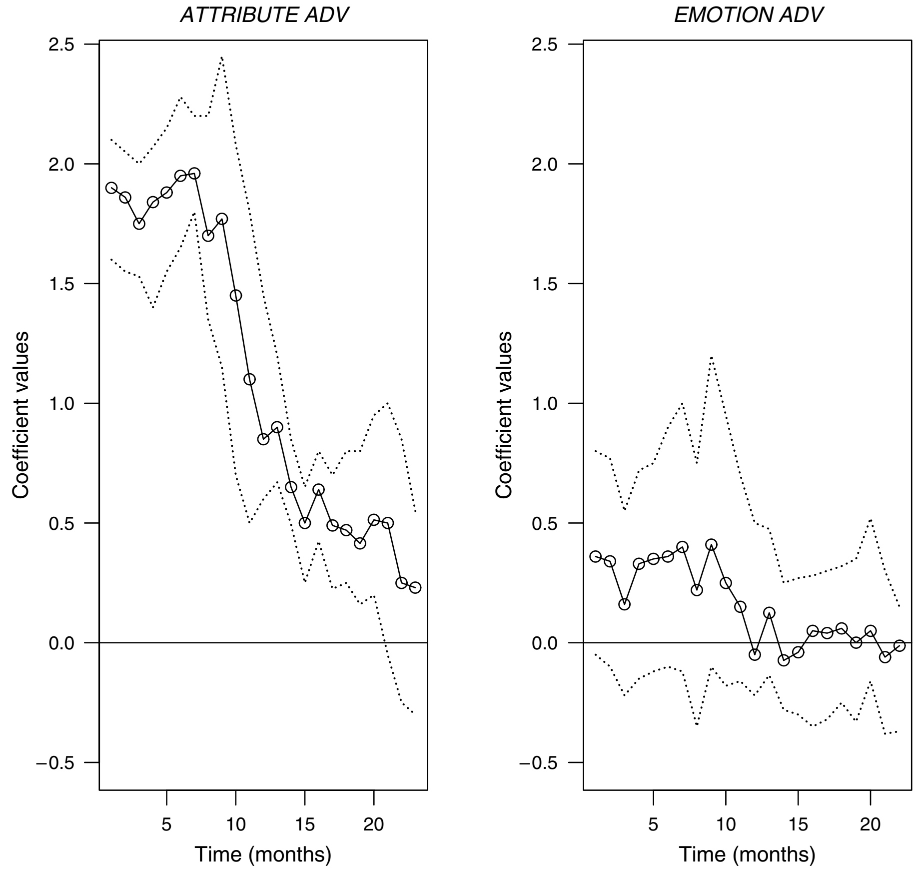
6. Discussion

There are several insights from our analysis that have implications for future research in this domain as well as the practice of marketing.

6.1. Research Insights

Each research insight is outlined below.

Figure 6(a) **Impact of Advertising on** ***ATTRIBUTE OWOM VALENCE*** **Over Time—Overall** (θ_t)



Notes. Solid lines represent the mean time-varying effect, whereas the 95% confidence intervals are depicted by dotted lines.

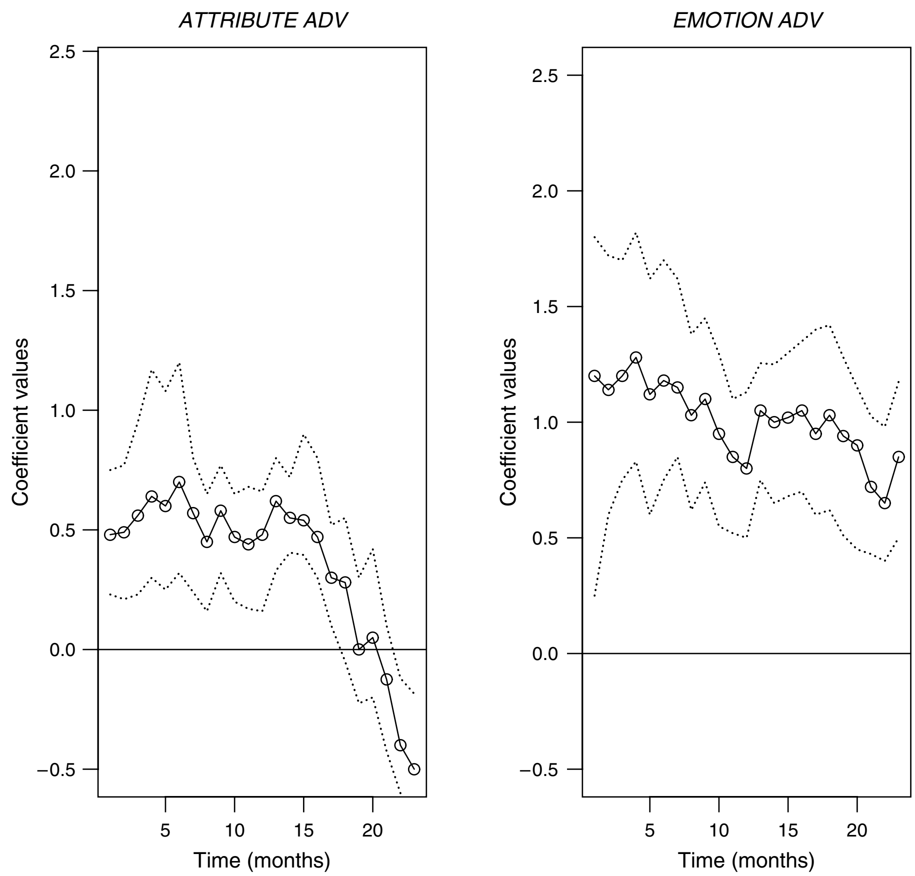
1. Using a dynamic modeling approach is critical to uncovering the evolving effectiveness of marketing communications. Specifically, not only are within-media changes captured but changes in relative effectiveness of different media forms can also be assessed. Our analysis shows that the DHLM methodology offers the most flexibility and best fit relative to the DLM, VAR/system of equations, or generalized Bass modeling approaches. Whereas the DLM approach provides several of the same benefits as the DHLM approach, we find that the pooling of information across brands enhances our model fit. Moreover, a unique advantage of the DHLM structure is the ability to estimate both the effect of the variables for each brand over time and an overall category effect over time.

2. This research is consistent with prior research that identified the dynamic effectiveness in traditional advertising (e.g., Sethuraman et al. 2011, Vakratsas and Ambler 1999), thus providing additional evidence of a media wearout phenomenon with traditional advertising. However, the current research extends this explanation to online word of mouth as well. Specifically, our findings raise the possibility of a wear-in and wearout behavior that occurs with different dimensions of OWOM. Our results suggest that emotion-oriented OWOM takes time to wear in before it is impactful and attribute-oriented OWOM wears out over time. The presence of these distinct effects further highlights the need for a dynamic modeling approach when examining media effectiveness.

3. All OWOM is not the same. Our research suggests that some OWOM has a direct impact on firm performance (*RECOMMENDATION OWOM VALENCE*), whereas other aspects of OWOM have an indirect impact on firm performance (*ATTRIBUTE OWOM VALENCE* and *EMOTION OWOM VALENCE*). From this outcome we would argue that OWOM is multidimensional and should not be one-dimensionalized. Rather, it should be dissected based on its content and each aspect analyzed to determine its unique dynamic impact.

4. Interactions across media may be driven by orientation of the media. Specifically, we find that different *forms* of media that have the same orientation (e.g., *emotion*-oriented OWOM and *emotion*-oriented advertising) can have a positive synergistic impact on firm performance. Thus, researchers should examine

Figure 6(b) **Impact of Advertising on** ***EMOTION OWOM VALENCE*** **Over Time—Overall** (θ_t)



Notes. Solid lines represent the mean time-varying effect, whereas the 95% confidence intervals are depicted by dotted lines.

the interaction effects between distinct media, paying particular attention to differences in both the content and the form of the media.

6.2. Marketing Management Insights

We outline each marketing-related insight below.

1. Research insights 1 and 2 raise the important issue of media timing. Specifically, from our analysis a marketing manager can begin to address the issue of timing of traditional media and how it may impact and interact with consumer-generated media. First, we find that traditional advertising, regardless of the

Table 6 **Parameter Estimates** (β_{bt})**—Brand-Level Comparsion**

	Mean impact on *SALES* [2.5th percentile, 97.5th percentile]					
	Online WOM content				Advertising content	
Brand	*RECOMMENDATION OWOM VALENCE*	*ATTRIBUTE OWOM VALENCE*	*EMOTION OWOM VALENCE*	*OWOM VOLUME*	*ATTRIBUTE ADV*	*EMOTION ADV*
Brand 1	0.84* [0.47, 1.26]	0.09 [−0.11, 0.30]	0.32* [0.09, 0.56]	0.14 [−0.05, 0.32]	0.26* [0.10, 0.44]	0.41* [0.18, 0.67]
Brand 2	0.71* [0.35, 1.17]	0.21* [0.03, 0.40]	0.15 [−0.04, 0.35]	0.27* [0.11, 0.44]	0.14 [−0.06, 0.36]	0.38* [0.17, 0.64]
Brand 3	0.38* [0.16, 0.62]	−0.03 [−0.25, 0.18]	0.04 [−0.19, 0.27]	0.02 [−0.21, 0.25]	0.57* [0.29, 0.73]	0.77* [0.41, 1.25]
Brand 4	0.46* [0.21, 0.77]	0.01 [−0.27, 0.29]	−0.02 [−0.23, 0.21]	0.06 [−0.15, 0.29]	0.44* [0.19, 0.68]	0.70* [0.33, 1.09]
Brand 5	0.61* [0.34, 0.97]	0.04 [−0.18, 0.25]	0.24* [0.09, 0.42]	0.11 [−0.08, 0.29]	0.37* [0.16, 0.63]	0.59* [0.31, 0.93]

*The 95% confidence interval does not include zero.

Table 7 Long-Term Impcts of Advertising and OWOM

	Long-term impacts
Online WOM	
RECOMMENDATION OWOM VALENCE	1.42* [0.94, 1.91]
ATTRIBUTE OWOM VALENCE	0.46* [0.17, 75]
EMOTION OWOM VALENCE	0.38* [0.11, 0.68]
OWOM VOLUME	0.29* [0.04, 0.55]
Advertising	
ATTRIBUTE ADV	0.84* [0.43, 1.27]
EMOTION ADV	1.59* [1.01, 2.06]

*The 95% confidence interval does not include zero.

orientation, wears out over time. Also, consistent with prior research, we observe that rational messages (i.e., attribute-oriented advertising) wear out a bit faster than emotion-oriented advertising.

Combating the wearout phenomenon, we find that consumer-generated media can help to drive sales via online recommendations. Firms have the greatest ability to influence these recommendations via emotion-oriented advertising. This type of advertising naturally also drives emotion-oriented OWOM. Although it takes time for emotion-oriented OWOM to wear in and become impactful, emotion-oriented OWOM can work synergistically with emotion-oriented advertising.

Thus, whereas firms might presume that attribute-oriented media should precede emotion-oriented media to inform consumers about the product features, our analysis suggests that both types of advertising are important, but the emotion-oriented advertising has a stronger effect on sales and wears out more slowly. In this research, we show this effect with OWOM, and it is consistent with researchers who have demonstrated this effect with traditional advertising (Hitchon et al. 1988, MacInnis et al. 2002). Given *all* of the dynamics within and between media forms, we propose that firms engage in emotion-oriented advertising early in the product life cycle so that it can become effective by the time the influences of rational media messages start to decline.

2. Perhaps one of the most counterintuitive outcomes from this analysis is that prior-period *OWOM VOLUME* does *not* drive sales or the valence of *RECOMMENDATION OWOM*. Thus, when examining OWOM, it is important to distinguish between *what* is said versus *how much* is said. Our data suggest that managers should focus on what is said and less on how much is said. This finding further suggests that using the amount of buzz is a weaker measure of the consumer's affinity for a brand as opposed to the quality of the buzz.

3. Firms' increasing focus on consumer recommendations raises the issue of what can be done to get a favorable recommendation. Our analysis suggests that not only is the absolute amount of online buzz less important but the firm's prior-period sales do not impact *RECOMMENDATION OWOM VALENCE*. The key lever that the firm can use to drive OWOM recommendations is emotion-oriented advertising. This is an important finding because it suggests that traditional media should not be neglected as newer forms of consumer engagement proliferate.

4. Brands differ with respect to the types of media that drive their sales. Through our dynamic model, we demonstrate that brands can be classified as being firm driven or consumer driven, depending on which type of media has the greatest impact on its sales. As new forms of media and customer engagement continue to evolve, this level of insight should be factored into marketing decisions. Furthermore, because media effectiveness is dynamic, we suggest that firms consider that this classification may evolve as brands persist in the market.

7. Conclusion

Although this research reveals insights with respect to traditional advertising, consumer-generated media, and the relationship between them, the strength of the research is grounded in our ability to relate these insights back to firm performance. Firms are beginning to realize that they need to keep track of OWOM conversations, yet this research confirms that traditional advertising media still plays an important role in the marketing of products. As firms embrace consumer-generated online media, we stress that they should not just focus on the volume of the media but pay attention to the content of the conversations as well.

Although this research extends our current knowledge, there are three research directions that may be worth pursuing further. First, we do not have website traffic data for this research. Although prior OWOM research in this area also has not investigated the role of website traffic data, we believe it could provide additional insights regarding the "demand" for OWOM content, i.e., product-specific website traffic. Second, in this research we are assuming exposure to different advertising channels to be the same. We make this assumption because channel-level exposure data at the brand-model level are unavailable. We believe it will be a worthwhile endeavor to incorporate channel exposure data into the framework. However, choosing an appropriate product category based on data availability could be a challenge. Third, it will be interesting to investigate the roles played by different forms of OWOM content (text, video, pictures, etc.) in driving firm performance. Moreover, we hope that future research will test our findings in other product categories as well.

In conclusion, we recommend that firms thoroughly investigate the dynamics within- and between-firm driven marketing communications and consumer-generated media. Our insights suggest that both traditional communication methods and consumer-generated OWOM interact to drive firm performance.

Appendix. Estimating Algorithm for the DHLM

We use a Gibbs sampler (Gelfand and Smith 1990) to sample from the following full conditionals for the different parameters.

1. *Full Conditionals for the Variance Parameters* (V_1, V_2, W). The variance parameters are given independent, inverted Wishart prior distributions. The resulting inverted Wishart posteriors for each of the variance parameters are given below:

$$\pi(V_1 \mid \beta, \theta, V_2, W) \propto \prod_{t=1}^{n} f_{\mathrm{N}}(y_t; F_t^T\theta_t, V_1) f_{\mathrm{IW}}(V_1; n_{V_1}/2, n_{V_1}S_{V_1}/2)$$
$$\propto f_{\mathrm{IW}}(V_1; n^*_{V_1}/2, n^*_{V_1}S^*_{V_1}/2)$$
$$\pi(V_2 \mid \beta, \theta, V_1, W) \propto \prod_{t=1}^{n} f_{\mathrm{N}}(\beta_t; D_t\theta_t, V_2) f_{\mathrm{IW}}(V_2; n_{V_2}/2, n_{V_2}S_{V_2}/2)$$
$$\propto f_{\mathrm{IW}}(V_2; n^*_{V_2}/2, n^*_{V_2}S^*_{V_2}/2)$$
$$\pi(W \mid \theta, V_1, V_2) \propto \prod_{t=1}^{n} f_{\mathrm{N}}(\theta_t; G_t\theta_{t-1}, W) f_{\mathrm{IW}}(W; n_W/2, n_W S_W/2)$$
$$\propto f_{\mathrm{IW}}(W; n^*_W/2, n^*_W S^*_W/2),$$

where

$$n^*_{V_1} = n_{V_1} + n, \quad n^*_{V_1}S^*_{V_1} = n_{V_1}S_{V_1} + \sum_{t=1}^{n}(y_t - F_t^T\beta_t)(y_t - F_t^T\beta_t)^T,$$
$$n^*_{V_2} = n_{V_2} + n - 1,$$
$$n^*_{V_2}S^*_{V_2} = n_{V_2}S_{V_2} + \sum_{t=2}^{n}(\beta_t - D_t\theta_t)(\beta 2_t - D_t\theta_t)^T,$$
$$n^*_W = n_W + n - 1,$$
$$n^*_W S^*_W = n_W S_W + \sum_{t=2}^{n}(\theta_t - G_t\theta_{t-1})(\theta_t - G_t\theta_{t-1})^T.$$

2. *Full Conditional for* β_t. Sequential inference is used for the sampling. For each time period we have a prior, posterior, and updated distribution for the parameters. The following is the updated posterior distribution:

$$\pi(\beta_t \mid \theta_t, V_1, V_2, W) \propto f_{\mathrm{N}}(y_t; F_t\beta_t, V_1) f_{\mathrm{N}}(\beta_t; D_t\theta_t, V_2)$$
$$\propto f_{\mathrm{N}}(\beta_t; \beta^*_t, C^*_t),$$

where

$$\beta^*_t = \left(\frac{F_t^T F_t}{V_1} + V_2^{-1}\right)^{-1}\left(\frac{F_t^T y_t}{V_1} + V_2^{-1}D_t\theta_t\right),$$
$$C^*_t = \left(\frac{F_t^T F_t}{V_1} + V_2^{-1}\right)^{-1}.$$

3. *Full Conditional for* θ_t. We sample from the full conditional using the forward filtering backward sampling algorithm proposed by Fruhwirth-Schnatter (1994) and Carter and Kohn (1994). Neelamegham and Chintagunta (2004) also implement a similar algorithm.

a. Forward filtering (sampling θ_n):

$$\pi(\theta_t \mid \beta^t) \propto \pi(\beta_t \mid \theta_t)\pi(\theta_t \mid \beta^{t-1})$$
$$\propto f_{\mathrm{N}}(\beta_t; D_t\theta_t, V_2) f_{\mathrm{N}}(\theta_t; a_t, R_t)$$
$$\propto f_{\mathrm{N}}(\theta_t; m_t, C_t),$$

where

$$m_t = a_t + A_t e_t, \quad C_t = R_t - A_t A_t^T Q_t, \quad A_t = \frac{R_t D_t}{Q_t},$$
$$e_t = \beta_t - f_t, \quad a_t = G_t m_{t-1}, \quad R_t = G_t C_{t-1} G_t^T + W,$$
$$f_t = D_t^T a_t, \quad Q_t = D_t^T R_t D_t + V_2.$$

b. Backward sampling (sampling θ_t, for $t = n-1, n-2, \ldots, 2, 1$):

$$\pi(\theta_t \mid \theta_{t+1}, V_1, V_2, W, y^t)$$
$$\propto \pi(\theta_{t+1} \mid \theta_t, V_1, V_2, W, y^t)\pi(\theta_t \mid V_1, V_2, W, y^t)$$
$$\propto f_{\mathrm{N}}(\theta_{t+1}; G_t\theta_t, W) f_{\mathrm{N}}(\theta_t; m_t, C_t)$$
$$\propto f_{\mathrm{N}}(\theta_t; (G_t^T W^{-1} G_t + C_t^{-1})^{-1}(G_t^T W^{-1}\theta_{t+1} + C_t^{-1}m_t),$$
$$(G_t^T W^{-1} G_t + C_t^{-1})^{-1}).$$

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