MITCHELL J. LOVETT, RENANA PERES, and RON SHACHAR*

Brands and word of mouth (WOM) are cornerstones of the marketing field, and yet their relationship has received relatively little attention. This study aims to enhance understanding of brand characteristics as antecedents of WOM by executing a comprehensive empirical analysis. For this purpose, the authors constructed a unique data set on online and offline WOM and characteristics for more than 600 of the most talked-about U.S. brands. To guide this empirical analysis, they present a theoretical framework arguing that consumers spread WOM on brands as a result of social, emotional, and functional drivers. Using these drivers, the authors identify a set of 13 brand characteristics that stimulate WOM, including three (level of differentiation, excitement, and complexity) that have not been studied to date as WOM antecedents. The authors find that whereas the social and functional drivers are the most important for online WOM, the emotional driver is the most important for offline WOM. These results provide an insightful perspective on WOM and have meaningful managerial implications for brand management and investment in WOM campaigns.

Keywords: word of mouth, brands, complexity, differentiation, esteem, online, offline

On Brands and Word of Mouth

Do differentiated brands get more or less word of mouth (WOM) than others? Does the level of differentiation matter in terms of WOM? What about the degree of a brand's complexity or its level of excitement? Extant research does not answer these questions. More broadly, although brands and WOM are cornerstones of the marketing field, the relationship between them has received relatively little attention. Although the literature has explored many aspects of the impact (e.g., Chevalier and Mayzlin 2006), dynamics (e.g., Yang et al. 2012), and social networking dimensions (e.g., Goldenberg et al. 2006; Katona, Zubcsek, and Sarvary 2011) of WOM, understanding of brand characteristics as antecedents to WOM is surprisingly limited. That is, the two broad literature streams on branding and WOM are largely distinct. Nevertheless, the role of brand characteristics in WOM is not only critical but also highly relevant for marketing scholars and practitioners for a variety of reasons, such as to create "talkable brands" and maximize the impact of branding activities (Rosen 2002; Word of Mouth Marketing Association [WOMMA] 2011).

This study aims to enhance the field's understanding of brand characteristics as antecedents of WOM by executing a comprehensive empirical analysis that examines the brand characteristics–WOM relationships for numerous brands. Specifically, we collected data on the 697 most talked-about U.S. national brands from 16 categories (e.g., food, media and entertainment, cars, financial services, sports), which include product and service brands, corporate brands, and product-specific brands. Our analysis is comprehensive not only because of the large number of brands but also because we incorporate both online and offline measures of WOM,

*Mitchell J. Lovett is Assistant Professor of Marketing, Simon Business School, University of Rochester (e-mail: mitch.lovett@simon.rochester.edu). Renana Peres is Lecturer (Assistant Professor) of Marketing, School of Business Administration, Hebrew University of Jerusalem (e-mail: peresren@huji.ac.il). Ron Shachar is Dean and Professor, Arison School of Business, Interdisciplinary Center Herzliya (e-mail: ronshachar@idc.ac.il). The authors thank their industry collaborators—Brad Fay from the Keller Fay Group, the NM Incite team, and Ed Lebar from Y&R's Brand Asset Valuator—for sharing their data. In addition, the authors thank Kristin Luck and the Decipher Inc. team for programming and managing the survey, Eitan Muller and Barak Libai for fruitful discussions, and the participants of the Marketing Science conference and the Yale Customer Insights conference. They are extremely grateful to their research assistants—at Wharton: Christina Andrews, Linda Wang, Chris Webber-Deonauth, Derric Bath, Grace Choi, Rachel Amalo, Yan Yan, Niels Mayrargue, Nathan Pamart, and Fangdan Chen; at Hebrew University of Jerusalem: Yair Cohen, Dafna Presler, Oshri Weiss, Liron Zaretzky, Anna Proviz, Tal Tamir, and Haneen Matar. This research was supported by the Marketing Science Institute, the Wharton Customer Analytics Initiative, the Israel Internet Association, Kmart International Center for Marketing and Retailing at the Hebrew University of Jerusalem, the Israel Science Foundation, and the Marketing Department at the Wharton School. Last, the authors thank the review team for their comments and insights. Jeffrey Inman served as associate editor for this article.

ISSN: 0022-2437 (print), 1547-7193 (electronic)

whereas existing research has typically relied on one or the other. Furthermore, previous scholars studying the antecedents of WOM have focused on only one or two brand characteristics; in our study, we evaluate the role of a broad set of brand characteristics.

To guide this empirical analysis, we begin by developing a theoretical framework that identifies brand characteristics that are relevant for WOM. This framework, whose fundamentals are consumers and the factors that stimulate them to engage in WOM, argues that consumers spread WOM for brands as a result of three drivers: social, emotional, and functional. The social driver relates to social signaling (i.e., expressing uniqueness, self-enhancement, and a desire to socialize), the emotional driver is related to emotion sharing, and the functional driver is related to the need to obtain and the tendency to provide information. Understanding these drivers and the needs associated with them helps us identify specific brand characteristics that play a role in stimulating WOM. Consider, for example, the social driver—specifically, the need to express uniqueness: it is easier to signal uniqueness through a highly differentiated brand than an undifferentiated brand. Consequently, we argue that a brand with a higher degree of differentiation is likely to have greater WOM. Notably, the potential role of differentiation on WOM has not yet been studied. Two additional characteristics that are novel to our study are a brand's level of excitement and its complexity.

Another layer of our analysis involves the heterogeneity of WOM across channels of communication. Specifically, the purpose and nature of WOM differ between offline conversations and online brand mentions. Whereas offline communication typically occurs in a one-to-one context and carries nonverbal clues, online communication is typically written and in a one-to-many context (i.e., read by a great number of people). Accordingly, we expect that the drivers' impact will differ between the two channels of communications as well.

Our empirical analysis rests on a comprehensive data set that includes the 697 most talked-about U.S. national brands. For each of these brands, we compiled data on offline and online WOM and, in line with our theoretical framework, on their characteristics. We gathered the brand characteristics data from (1) a survey we conducted on a representative U.S. sample with 4,769 respondents (on characteristics such as complexity and excitement) and (2) the proprietary Y&R data based on its Brand Asset Valuator panel (on characteristics such as differentiation). The data on the offline WOM are from the Keller Fay group (Keller 2007) and include a weekly measure of the offline WOM (i.e., face-to-face and telephone conversations) for more than 1,000 brands mentioned from January 2007 to August 2010. The online data are from the former Nielsen and McKinsey NM Incite's tool, and they include a daily measure of the online WOM (i.e., blogs, user forums, and Twitter messages) for each of these brands between 2008 and 2010.

Our analysis of this cross-sectional data not only provides empirical support for the relationship between brand characteristics and WOM but also demonstrates that each of the drivers identified in our theoretical framework (social, emotional, and functional) is relevant and significant in this process. Furthermore, each of the characteristics this framework introduces to the WOM discussion (differentiation, complexity, and excitement) has a significant relationship with WOM. For example, we find that brands that are highly differentiated from others (and thus enable consumers to express their uniqueness) have, as expected, more WOM. Notably, this effect is much stronger in the online setting than in offline conversations.

Indeed, the results also reveal insightful differences between online and offline WOM at the brand characteristic level. In some cases, characteristics have a significant effect in one setting but not in the other (e.g., age of brand). These discrepancies at the brand characteristic level are indicative of differences with respect to the importance of the three overall drivers. We find that whereas the social and functional drivers are the most important for online WOM, the emotional driver is the most important for offline WOM. These results paint a unique picture of WOM. Offline conversations, which typically occur in one-on-one settings, are inherently more personal and intimate and thus enable people to share emotions such as excitement and satisfaction. Online WOM, which usually involves "broadcasting" to many people (e.g., Twitter), may be more appropriate for social signaling (e.g., emphasizing uniqueness).

Our work not only reveals new findings; it also has managerial implications. Brand managers could leverage our results to help diagnose their brands' WOM performance. For example, our model could be used to identify brands that, given their characteristics, underperform in terms of WOM in the sense that their actual WOM is lower than the level predicted by the model. Such a gap might be due to various sources, one of which is that the brand has not lived up to its WOM potential, which might suggest a reexamination of the firm's WOM strategy. To assist managers in diagnosing their brands' WOM performance, we created a model-based Descriptive Decision Support System (DDSS) in Microsoft Excel (Power and Sharda 2009).

THEORETICAL FRAMEWORK

This section introduces our theoretical framework, which we then use to identify brand characteristics that are relevant for WOM. We begin with the most fundamental elements: consumers and the factors that stimulate them to engage in WOM. Building on previous research, we argue that consumers spread brand WOM for three fundamental purposes: social, emotional, and functional. The main social driver is the desire to send signals to others about one's expertise, uniqueness, or social status; the emotional driver is the need to share positive or negative feelings about brands to balance emotional arousal; and the functional driver motivates people to provide and supply information. There may be additional drivers, but drawing on previous research, we consider these three the major ones.

We use the term "theoretical framework" rather than "theory" or "model" to reflect its role adequately in this study. This study's main contribution rests on the data and findings, and the central role of the theoretical framework is to guide the empirical analysis by identifying and organizing brand characteristics that might be relevant for WOM as well as by suggesting possible interpretation for the results.

Next, we discuss in more detail the relevant literature and the three fundamental drivers and identify their relevant brand characteristics. For clarity, the brand characteristics that are included in our model are in italics.

The Social Driver

Self-enhancement. A compelling social motive to engage in WOM is self-enhancement. Wojnicki and Godes (2011) show that consumers strategically use WOM to signal or enhance their perceived expertise. To achieve this purpose, positive WOM is more effective than negative, because experts are expected to identify high-quality products better than novices. Thus, consistent with prior evidence (Amblee and Bui 2008), it is expected that the higher the esteem or *quality* associated with the brand, the more likely consumers are to engage in WOM about it. Another aspect of self-enhancement is status signaling. People use their purchases to signal their social status to others, either to their own social group or to other groups (Han, Nunes, and Drèze 2010) such that luxury goods signal a high social status (Veblen 1994 [1899]). We suggest that consumers can signal a high social status not only by purchasing but also by talking about luxury goods. Therefore, we hypothesize that brands that are perceived as *premium* will generate a higher level of WOM than what people refer to as value brands.

Expressing uniqueness. Previous studies have demonstrated that consumers use consumption and possessions to express their uniqueness or their group identity (e.g., Berger and Heath 2007), but surprisingly, researches have ignored the possibility of employing WOM for this purpose.[1] We suggest that consumers can also express their uniqueness by talking about brands. Furthermore, we posit that some brands are better suited to express uniqueness than others. Specifically, brands that are highly differentiated from others more easily enable consumers to project a unique identity or membership in a group. Therefore, we hypothesize that the higher the degree of a brand's *differentiation*, the more likely it is to generate WOM.

Desire to converse. The basic human desire to socialize, and thus converse, with others (Rosen 2002; Rubin, Perese, and Barbato 1988) can lead to WOM. Berger and Schwartz (2011) demonstrate empirically that a brand's visibility facilitates people's ability to use it in a conversation. Thus, our model will account for the brand's *visibility* or observability. Another attribute that may make a brand suitable for conversation is whether it is relevant in the lives of many people. For example, an indie band is less likely to be conversation material than a mainstream band.[2] Consequently, we expect that as brands become more *relevant* to more people, they are more likely to spark conversation.

The Emotional Driver

Consuming or thinking about a brand can evoke emotions that people might like to share with others (Heath, Bell, and Sternberg 2001; Nardi et al. 2004; Peters and Kashima 2007) to express or ease emotional arousal (Berger and Milkman 2012). Previous studies have focused on the role of one emotion in this context: *satisfaction*. They provide evidence that brands that evoke both very high (Roberts 2004) and very low (Richins 1983) satisfaction levels receive higher levels of WOM than brands with moderate levels of satisfaction.

Notably, the role of a brand's *excitement* (one of the five brand personality traits introduced in Aaker 1997) has been overlooked in this context. However, excitement is certainly a stimulating emotion that can be expressed through conversation, and thus, it is reasonable to expect that the higher the brand's excitement factor, the more likely people are to engage in WOM about it.

The Functional Driver

People may exchange useful and practical information through conversation, and brands are often the subject of that information exchange. In any such exchange, there is a person who needs the information and one who provides it. We proceed by discussing these two sides.

Information demand. Previous studies have suggested that consumers' need for information is especially high for new brands because the uncertainty associated with them is higher (for a review, see Peres, Muller, and Mahajan 2010). Furthermore, existing evidence indirectly suggests that WOM decreases over the life of a brand (Godes and Mayzlin 2004). Accordingly, we include the *age* of the brand and directly test whether WOM is greater for newer brands.

Whereas previous studies have focused on the newness of the brand as a source of uncertainty, we suggest that another characteristic (heretofore ignored by previous studies on WOM) might be in play: the brand's *complexity*, or the difficulty of obtaining and comprehending information about it. We hypothesize that the greater the complexity, the greater the brand's WOM. Note that although prior research has ignored the relationship between this characteristic and WOM, it has been discussed in the context of diffusion of innovations (Rogers 1995).

The demand for information might also depend on the *type of good*, be it an experience, search, or credence good (Anand and Shachar 2011; Mudambi and Schuff 2010). In this context, WOM can be useful for exploring intangible attributes of experience goods (e.g., ambience in a restaurant) and for keeping up to date on observable attributes of search goods (e.g., new service plans with AT&T). Whether search goods, experience goods, or credence goods stimulate more WOM, however, is an open empirical question.

Information supply. Previous studies have identified motives to provide information (e.g., altruism, reciprocity). For a consumer to provide information and engage in conversation about a brand, it must be familiar to him or her. Thus, we hypothesize that a higher level of familiarity (Sundaram and Webster 1999) or *knowledge* about a brand will be associated with more WOM.

Hybrid Characteristics

Two additional brand characteristics discussed in previous studies, *involvement* (Dichter 1966; Sundaram, Mitra, and Webster 1998) and *perceived risk* (Lutz and Reilly 1974; Sundaram, Mitra, and Webster 1998), do not fit well into a single driver. Involvement can be both functional and emotional: it can be functional because people are likely to seek more information about high-involvement products,

[1]Previous studies that have examined the interaction between WOM and expression of uniqueness have had very different foci. Ho and Dempsey (2010) show that people who stand up to others report that they are more likely to forward online content. Che, Lurie, and Weiss (2011) demonstrate that people who want to communicate their expertise have a higher tendency to reply to online requests for advice. Cheema and Kaikati (2010) find that people with high need for uniqueness refrain from engaging in WOM to keep others away from "their" products.

[2]This should be true even when we take into account that a fan of an indie band is likely to have similar friends. Even in the fan's personal life, there are probably many people who are not likely to be fans of indie bands.

and it can be emotional because some commonly used scales of involvement include items such as "means a lot to me" (Zaichkowsky 1985), which reflect emotions that people may feel the need to share. Similarly, perceived risk can also be mapped into both the functional and the emotional drivers. Rogers (1995) discusses three aspects of risk: the actual performance of the brand, the extra expenses that might be incurred, and the social embarrassment the brand might cause. Although each of these risks might motivate consumers to seek information to resolve them, they might also induce anxiety that consumers may want to express, as explained by Sundaram, Mitra, and Webster (1998), who focus on this emotional aspect of risk.

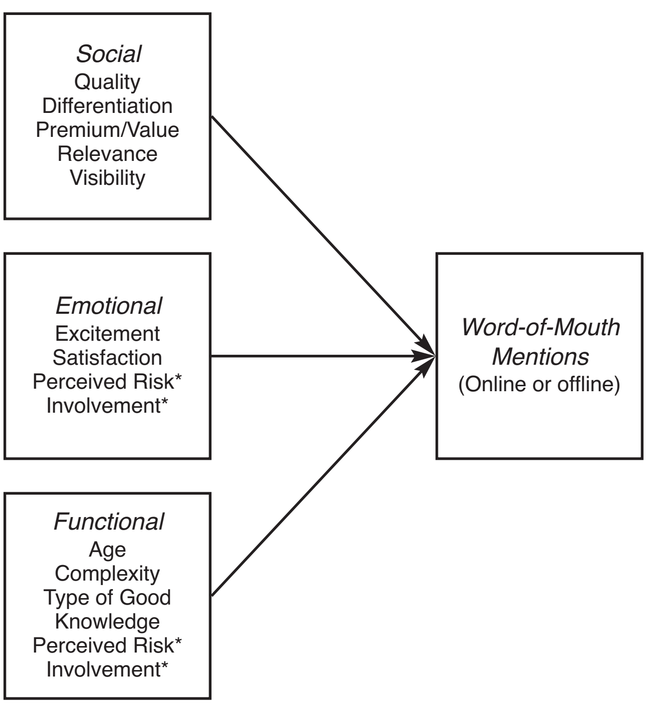
As we discuss subsequently, some of our empirical analysis is intended to evaluate the relative importance of the three fundamental drivers. The classification of two characteristics as both functional and emotional complicates this analysis. To address this issue, we execute the analysis both with and without the hybrid characteristics to demonstrate robustness.

Figure 1 illustrates our theoretical framework, including the three fundamental drivers—social, emotional, and functional—and the associated brand characteristics. We propose that these brand characteristics affect the level of WOM. In the following subsection, we describe our measures and data collection procedures for these brand characteristics and for WOM on both online and offline channels.

Online Versus Offline

Thus far, we have discussed WOM without distinguishing offline conversations and online mentions. However, it is reasonable to assume that the purpose and nature of WOM differ between the two environments. First, offline meetings are more intimate and personal than online interactions because, unlike online interactions in which a person "broadcasts" a message to many (e.g., Facebook, Twitter), offline conversations frequently occur in a personal one-on-one setting (Hoffman and Novak 1996; Morris and Ogan 1996). Second, in offline meetings (especially those that are face-to-face), the communication extends beyond spoken words. For example, people can use tone, facial expressions, and body language to convey thought. Third, offline interactions are more interactive (or "synchronous," in communications terminology), in the sense that the other conversation parties are expected to respond, usually immediately (Morris and Ogan 1996). In contrast, online channels such as blogs, user forums, and Twitter are, in many cases, unidirectional and asynchronous, with no immediate response (if any).

Figure 1
THEORETICAL FRAMEWORK: MATCHING WOM DRIVERS, BRAND CHARACTERISTICS AND WOM



*Hybrid characteristics.

As a result of such differences, it is reasonable to expect that the roles of the drivers and characteristics differ between the two communication media. Consider the three characteristics that have not previously been studied as WOM antecedents: differentiation, excitement, and complexity. As we discussed, differentiation enables consumers to express their uniqueness. Because in most online interactions, (1) the format is one of broadcasting to many (Morris and Ogan 1996) and (2) interactions are more likely to take place with unfamiliar people (Walther 1996), the tendency to express personal aspects in general, and uniqueness in particular, should be greater. Furthermore, the ability to express uniqueness nonverbally is greater in an offline setting than in online interactions (Illouz 2007, chap. 3). For example, when a person wears a shirt from a highly differentiated brand, he or she need not mention it in an offline conversation. As a result of these two factors, differentiation might be expected to play a more important role in online versus offline interactions.

In contrast, the relative role of excitement is likely to be stronger in offline meetings than in online interactions due to the intimate and personal nature of the former. In addition, when excited, people might seek immediate responses and feedback from their conversation partners; therefore, they might prefer to use the more interactive and synchronous offline medium. As a result, we expect excitement to be stronger offline than online.

Finally, the impact of complexity is likely to be stronger in offline meetings than in online interactions due to the interactivity of the offline medium as well as the ability to ask and answer questions, which helps people comprehend complex brands. This stands in contrast to online communications, which are not only asynchronous but also sometimes limited in length (e.g., Twitter, user forums) and thus restrict thorough discussion.

Although (1) we do not offer a clear theory on this matter and (2) the focus of our study is not to understand these differences, per se, we study the effect of brand characteristics on online and offline WOM separately to avoid misspecification of the model. We also aim to provide some initial empirical insights on this issue.

DATA

To study the role of brand characteristics in stimulating WOM, we used several sources to build a comprehensive data set containing information about WOM as well as brand characteristics for 697 major U.S. national brands spanning 16 broad product categories (for the full list of brands and categories as well as the data set's construction, see Web Appendix A at www.marketingpower.com/jmr_webappendix).[3] The categories are beauty products, beverages, cars, children's products, clothing products, department stores, financial services, food and dining, health products, home design and decoration, household products, media and entertainment, sports and hobbies, technology products and stores, telecommunication, and travel services. The brands' heterogeneity is high, including both corporate and product brands. These include consumer brands (e.g., Coca-Cola, Dove), service brands (e.g., Expedia, Charles Schwab, Burger King), sports teams (e.g., the Boston Celtics), and television shows (e.g., *CSI: Crime Scene Investigation*). For each brand, we collected data on WOM, brand characteristics, and relevant control variables. Figure 2 describes our complete set of data sources, which we describe in detail in the following subsections.

WOM Data

We group the variety of channels through which WOM can be distributed and consumed into two main categories: offline channels, such as face-to-face and telephone conversations, and online channels, such as blogs, e-mails, user reviews, virtual social networks, user forums, and microblogs (e.g., Twitter). We collect data on the overall number of brand mentions during the study's time period for both channel categories and conduct our analysis on the two categories separately.

Offline WOM. The Keller Fay Group's TalkTrack project is the industry's most accepted measure of offline WOM (e.g., it is used by WOMMA). This is a diary-style survey of a representative sample of the U.S. population. Every week, 700 different respondents are asked to conduct a 24-hour diary in which they document WOM incidents, including every face-to-face or phone conversation they have in which a brand is mentioned. Then, they list the brands mentioned in the conversation. Note that a list of brands is not provided to respondents (i.e., they can mention any brand). For each brand, we aggregated the number of mentions between January 2007 and August 2010 and included both telephone and face-to-face conversations. The average number of mentions in our data is 805, and the brand with the highest number (15,038) is Coca-Cola.

Online WOM. The source for the online WOM data is the tool used by Nielsen McKinsey's NM Incite (formerly BuzzMetrics), a search engine that has conducted daily searches through blogs, discussion groups, and microblogs since July 2008 and processes all available posts for each of these sources.[4] As with the offline data, we aggregated the data across time (July 2008 to March 2010) and online sources. The average number of online mentions in our data is approximately 430,000, and the brand with the greatest number of mentions (14,579,172) is Google.

Table 1 displays the top ten brands online and offline. Note that these include both product brands, such as iPhone and Xbox 360, and corporate brands, such as Sony and AT&T. Only one brand, Ford, appears in both lists, illustrating the differences between these two WOM channels. Table 2 presents the distribution of mentions across the 16 categories. For each category, it shows the number of brands and the average number of mentions per brand for offline and online settings.

The way we obtained the brand mentions differs between the two channels. For the offline data, we used a sample of

[3]We compiled this list on the basis of our WOM data to capture the most talked-about brands in the United States between 2007 and 2010.

[4]Operating this search engine requires the user to build queries that include the brand and related words to retrieve the relevant information and distinguish the brand from unrelated mentions of the same name (e.g., some brand names are also everyday words, such as the television show *House* or Gap clothing stores). In addition, the tool excludes automatic reposts, such as retweets. We also manually checked a large sample of posts and found that more than 95% seemed to be user generated.

Figure 2

THE LIST OF DATA SOURCES

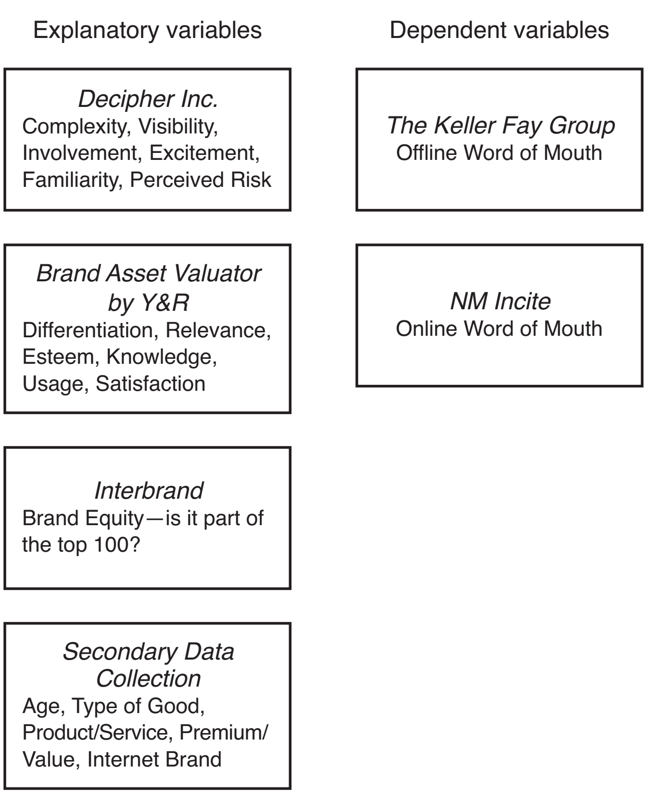


Table 1

TOP TEN MOST MENTIONED BRANDS OFFLINE AND ONLINE

Order	*Offline*	*Online*
1	Coca-Cola	Google
2	Verizon	Facebook
3	Pepsi	iPhone
4	Wal-Mart	YouTube
5	Ford	eBay
6	AT&T	Xbox 360
7	McDonald's	Ford
8	Dell	Yahoo!
9	Sony	Disney
10	Chevrolet	Audi

Table 2
DISTRIBUTION OF TOTAL MENTIONS AND MENTIONS PER BRAND, OFFLINE AND ONLINE

Category	Number of Brands	Percentage of Total Mentions: Online	Percentage of Total Mentions: Offline	Average Number of Mentions per Brand: Online	Average Number of Mentions per Brand: Offline
Beauty products	52	1%	5%	53,205	526
Beverages	66	3%	13%	150,536	1,129
Cars	47	17%	10%	1,005,732	1,213
Children's products	19	0%	2%	70,730	579
Clothing products	51	3%	7%	150,952	777
Department stores	15	4%	5%	695,945	1,779
Financial services	39	2%	4%	113,656	621
Food and dining	105	4%	12%	115,139	620
Health	27	1%	3%	140,630	534
Home design	13	1%	2%	114,670	654
Household products	24	0%	2%	28,327	475
Media and entertainment	103	32%	9%	893,706	476
Sports and hobbies	21	8%	3%	1,110,863	707
Technology	56	17%	12%	847,929	1,248
Telecommunications	25	7%	9%	776,423	1,961
Travel services	34	1%	3%	60,305	543

Notes: The sample contains only the most talked-about brands. The online numbers contain mentions from all the available sources, whereas the offline numbers only contain mentions from a weekly representative sample of 700 people. As a result, the numbers for offline cannot be directly compared with those for online.

people, whereas in the online data, we use a sample of posts. This means that for the online data (like previous studies that use online WOM data), we do not observe the receiving side of the communication but rather only the "sender." For some purposes, this would mean a selection bias. For example, if we were measuring individual-level propensities to engage in WOM, our sample has problems. However, for our purposes—to measure aggregate brand mentions online—this sample is appropriate. Another possible difference between these two data sets is that different types of people use the two channels. We acknowledge that differences in the role of brand characteristics between the channels could be due to these dissimilarities in people rather than in the channel, per se. After presenting our results, we discuss some ways that future studies could leverage more refined measures to provide a more disaggregate picture of WOM behaviors.

Brand Characteristics

To operationalize the brand characteristic variables identified in Figure 1, we used existing measurement scales (e.g., Aaker's brand personality) whenever possible. To collect the data, we conducted a large-scale original data collection using several existing public and proprietary databases. We then combined these sources (see Figure 2).

The first source is Y&R's proprietary database, the Brand Asset Valuator (YRBAV). It measures brand equity on four perceived dimensions (termed "pillars" by the company): energized differentiation, relevance, esteem, and knowledge. Y&R constructs this data set from a quarterly panel survey that measures a broad array of perceptions and attitudes for a large number of brands, including 629 of the 697 brands we consider. From this survey, Y&R builds the four pillars for each brand.

The second major source of data is from a survey we developed and administered to a representative sample of the U.S. population through Decipher Inc.[5] We collected data from 4,769 respondents on product involvement and brand familiarity, excitement, complexity, visibility, and perceived risk.

In addition, we used several other secondary sources. First, we used Interbrand data on the brands ranked in their "Top 100 Brands" list over the preceding few years. Second, we used the American Customer Satisfaction Index (ACSI) to measure brand-level satisfaction. Third, we used secondary data sources to code several other variables, such as age and type of good. Next, we describe our variables, scales, and measures in detail; their summary statistics appear in Table 3.

Age. We define age as the time elapsed from the commercial launch of the brand to the reference current date, August 1, 2010. We obtained the data from brand publications and from historical business and press data. Our oldest brand is Colgate, launched in 1806, and the newest is the movie *Transformers: Revenge of the Fallen*, released on June 29, 2009.

Type of good. We used Nelson's (1974) and Laband's (1986) classifications to divide the brands into search, experience, and credence goods. We operationalize this measure, as originally defined, at a subcategory level between the category and brand levels. For example, health clubs and sports teams are subcategories within the category of sports and hobbies. Using the definitions from the literature, two independent judges separately classified the subcategories. The intercoder agreement was 72%, and the judges resolved all disagreements by consensus.

Complexity. We measured complexity in our survey using a five-point scale based on Moore and Benbasat (1991) and Speier and Venkatesh (2002). Our complexity scale includes items regarding (1) the learning efforts needed to acclimate to the brand, (2) the time required to fully understand its advantages, (3) the difficulty of the product concept, and (4) the mental effort required to use the brand (for our exact questions, see Web Appendix B at www.marketingpower.com/jmr_webappendix). In our brand list, Medicare is perceived as the most complex brand and Pledge as the least complex.

Knowledge. We used two variables to measure the level of knowledge about the brand. The first, familiarity, is a single-item, five-point scale included in our survey that asks respondents to what extent they are familiar with the brand. The second variable, knowledge, is one of YRBAV's pillars. It is a single-item, five-point scale that asks respondents to indicate their level of intimate understanding of the brand. As Table 3 indicates, brands such as Band-Aid and Wal-Mart rank high on familiarity and knowledge, whereas more local brands, such as H-E-B Grocery and Shaw's supermarket, rank low. These two variables, though similar, differ in how detailed or intimate the knowledge is. The correlation between these

[5]Decipher Inc. is a California-based company that specializes in developing and managing large-scale surveys. The questionnaire began with screening questions about the respondent's level of familiarity with the category and the brands. Then, the system chose several brands with which the respondent indicated familiarity and asked about the product and brand attributes. The system dynamically allocated brands to respondents until we reached 35–40 responses on each of our 697 brands. We describe an annotated version of this complex questionnaire in Web Appendix B (www.marketingpower.com/jmr_webappendix).

Table 3
SUMMARY STATISTICS

	M	*SD*	*Min*	*25%*	*50%*	*75%*	*Max*	*Maximum Value Brand*	*Minimum Value Brand*	*Observations Used*
Dependent										
Online brand mentions (/1,000,000)	.43	1.12	0	.03	.08	.33	14.58	Google	Vault Energy Drink	613
Offline brand mentions (/1,000)	.86	1.46	.12	.24	.41	.84	15.04	Coca-Cola	*America's Got Talent*	613
Social										
Differentiation	.49	.16	.17	.39	.46	.57	1.12	Food Network	Days Inn	613
Esteem	.61	.30	.09	.38	.55	.77	1.67	Tylenol	*Ugly Betty*	613
Middle (premium/value)	.51	.5	0	0	1.00	1.00	1.00			613
Premium (premium/value)	.26	.44	0	0	0	1.00	1.00			613
Relevance	2.74	.72	1.39	2.13	2.65	3.24	4.75	Kraft	Saab	613
Visibility	3.01	.37	1.79	2.78	3.02	3.27	3.99	Microsoft	Lamborghini	613
Emotional										
Excitement[a]	3.28	.40	2.05	3.00	3.27	3.54	4.51	iPhone	Medicare	613
Satisfaction (/50)	1.59	.13	1.1	1.5	1.63	1.69	1.79	Heinz	Charter Communications	201
Functional										
Age (/50)	1.11	.76	.04	.5	.96	1.61	4.09	Colgate	*Transformers: Revenge of the Fallen*	613
Search	.21	.41	0	0	0	0	1			613
Credence	.07	.25	0	0	0	0	1			613
Complexity	1.82	.38	1.01	1.53	1.81	2.06	3.03	Medicare	Pledge	613
Familiarity	3.36	.59	1.48	2.92	3.42	3.79	4.62	Band-Aid	H-E-B Grocery	613
Knowledge	3.54	.88	.73	3.02	3.71	4.18	5.16	Wal-Mart	Shaw's	613
Hybrid										
Perceived risk	1.79	.31	1.02	1.54	1.81	2.01	2.62	Medicare	Dr. Pepper	613
Involvement	3.72	.36	3.09	3.52	3.62	3.97	4.38	Financial services	Beverages	613
Controls										
Interbrand top 100	.12	.33	0	0	0	0	1.00			613
Usage (/50)	.67	.45	.01	.29	.58	1.00	1.79	Band-Aid	Porsche	613
Mixed (product/service)	.03	.17	0	0	0	0	1.00			613
Service (product/service)	.43	.50	0	0	0	1.00	1.00			613
Internet brand	.03	.16	0	0	0	0	1.00			613

[a]This is the average of the two excitement items from the Aaker questionnaire as described in the “Data” section.

variables is .80. Therefore, we use principal component analysis to identify a single factor to incorporate both these variables. This one factor explains 91% of the variation, and both variables load positively (for details, see Web Appendix C at www.marketingpower.com/jmr_webappendix).

Differentiation. To measure differentiation, we used the YRBAV pillar energized differentiation. Energized differentiation is a weighted average of items indicating to what extent the product is different, distinctive, unique, dynamic, and innovative, a fairly direct of measure of differentiation. Of our list of brands, Food Network has the highest differentiation score, and Days Inn has the lowest.

Relevance. We measure how relevant a brand is to a broad set of people with the YRBAV pillar relevance. This pillar measures the percentage of people who stated that the brand is personally appropriate for them. Kraft is the most relevant on our list, and the car brand Saab is the least.

Quality. We measure quality through the final YRBAV pillar, esteem. This variable captures the extent to which people hold a brand in high esteem. We measured this variable through items asking about the leadership, reliability, and quality of the brand. Tylenol has the highest esteem score and the prime-time television soap opera *Ugly Betty* has the lowest.

Premium. Two independent judges classified each brand as one of the following: premium, value, or middle. The intercoder agreement was 70%, and the judges resolved all disagreements by consensus. They classified brands relative to the product type (e.g., they evaluated Clinique relative to beauty products and Hilton with respect to other hotels). In formulating these classifications, the judges used secondary data on various aspects such as the relative price to the category.

Visibility. We measure visibility as Rogers's (1995) observability construct, using a five-item, five-point scale based on Moore and Benbasat (1991). These survey items determine whether respondents commonly see the brand in their environment. The brand with the highest visibility on our list is Microsoft, and Lamborghini received the lowest visibility score.

Excitement. We included in our survey a subset of Aaker's (1997) five-point excitement scale, which includes items such as "exciting" and "spirited." The full scale comprises items that overlap with other variables in our analysis (e.g., age, differentiation) and, as a result, leads to inflated standard errors (i.e., multicollinearity). Note that our qualitative results do not change if we use the full excitement scale. As Table 3 indicates, the most exciting brand on our list is iPhone and the least exciting is Medicare.

Satisfaction. We use the ACSI, a standard measure of satisfaction for American corporate brands (Fornell et al. 1996). The measure is a 0–100 index collected each quarter using 250 customer telephone interviews per brand on a rolling set of brands, with each receiving at least one measure each year. Of our list of brands, 209 have an ACSI score (with Heinz having the highest score and Charter Communications the lowest). Subsequently, we discuss how we handled this missing data challenge.

Perceived risk. Rogers (1995) defines perceived risk as the functional, financial, and emotional uncertainty associated with the product (in which emotional uncertainty is the feeling of social embarrassment that might be associated with using the brand). We use the full three-item, five-points scale (Ostlund 1974) and collect this measure of perceived risk in our survey. Of our list of brands, Medicare has the highest perceived risk score, and Dr. Pepper is perceived as the least risky.

Involvement. To measure involvement, we use Ratchford's (1987) three-item, five-point scale. The items measure the importance of the purchase decision, the amount of thought invested in the decision, and the consequences of making the wrong decision. In line with prior studies, our measure of involvement (collected by survey) is at the category level. In a preliminary check, we measured involvement at the brand level but observed little variation between brands within a category. Of our 16 categories, financial services have the highest involvement level and beverages have the lowest.

Control Variables

We also include control variables to account for a variety of other concerns. For example, one might argue that people talk about some brands simply because these brands are widely used or have existing brand equity (e.g., high media coverage or ad budgets).

Brand equity. We use data from Interbrand to measure brand equity and to capture advertising and media coverage effects. Using Interbrand's list of top 100 brands from 2008–2010, we code a binary variable indicating whether the brand is on the list. We expect brand equity to increase WOM.

Usage. To gauge usage, we use a measure from YRBAV's survey of the percentage of people who answered that they use the brand frequently or occasionally. Band-Aid is scored the highest on usage and Porsche is scored the lowest.

Product/service. Two independent judges classified each brand on the list to one of the following: product, service, or mixed. The judges used the four criteria of Parasuraman, Zeithaml, and Berry (1985): intangibility, inseparability (of production and consumption), perishability (cannot be inventoried), and heterogeneity (difficult to standardize). Accordingly, the judges classified video games and movies as products, fashion brands that are sold both in their own stores and in other outlets as mixed, and sports teams as services. The intercoder agreement was 82%, and the judges resolved all disagreements by consensus.

Internet brand. Seventeen of the brands on our list, including eBay, Amazon, Expedia, and Google, are Internet-based services and, thus, by their nature might be more relevant for online than WOM. To control for this factor, we code a binary variable indicating whether the brand is an Internet brand.

Final Sample and Data Summary

Some of the brands included in our initial list (i.e., the top 700 talkable brands) are not included in the final sample because many of our variables are not available for them. For example, movies and television programs and some subbrands (e.g., Cherry Coke) do not have data available for satisfaction or any of the YRBAV variables. As a result, our final sample contains 613 brands. For these brands, we have complete data on all variables but satisfaction (which is available for only 209 brands). This final data set contains two dependent variables, online and offline brand mentions (WOM), and 19 explanatory variables. Table 3 displays summary statistics for the dependent and explanatory variables, and Table 4 presents the correlations for the

Table 4
CORRELATIONS

	Different-iation	*Esteem*	*Middle (Premium/Value)*	*Premium (Premium/Value)*	*Relevance*	*Visibility*	*Excite-ment*	*Satisfaction*	*Age (/50)*	*Search*	*Credence*	*Complexity*	*Knowledge Factor*	*Perceived Risk*	*Interbrand Top 100*	*Usage (/50)*	*Mixed (Product/Service)*	*Service (Product/Service)*	*Internet Brand*
Differentiation	1	.10	–.15	.3	–.01	.09	.57	.19	–.31	.10	–.15	.12	0	.07	.22	–.03	.17	–.09	.11
Esteem	.10	1	.05	–.05	.80	.51	–.15	.23	.35	.04	–.03	–.42	.68	–.49	.22	.58	–.03	–.25	–.01
Middle (premium/value)	–.15	.05	1	–.58	.04	.09	–.15	–.16	.07	.02	.17	–.02	.02	–.06	.01	0	.03	–.12	.08
Premium (premium/value)	.30	–.05	–.58	1	–.17	–.10	.26	.17	–.03	0	–.09	.17	–.11	.13	.08	–.16	.01	.04	–.05
Relevance	–.01	.80	.04	–.17	1	.54	–.20	.25	.25	.03	–.11	–.62	.70	–.67	.08	.85	–.07	–.18	0
Visibility	.09	.51	.09	–.10	.54	1	.07	.13	.11	.07	–.15	–.50	.51	–.50	.17	.45	.01	–.2	–.06
Excitement	.57	–.15	–.15	.26	–.20	.07	1	.24	–.29	.10	–.20	.08	–.10	.02	.07	–.13	.09	–.07	–.01
Satisfaction	.19	.23	–.16	.17	.25	.13	.24	1	.13	.07	–.10	–.54	.23	–.60	.06	.23	.03	–.61	–.18
Age (/50)	–.31	.35	.07	–.03	.25	.11	–.29	.13	1	–.01	.09	–.16	.24	–.18	.11	.14	–.01	–.12	–.16
Search	.10	.04	.02	0	.03	.07	.10	.07	–.01	1	–.13	.02	–.03	.04	.08	.01	.13	–.15	–.06
Credence	–.15	–.03	.17	–.09	–.11	–.15	–.20	–.10	.09	–.13	1	.31	–.17	.17	–.02	–.18	–.05	.12	.07
Complexity	.12	–.42	–.02	.17	–.62	–.50	.08	–.54	–.16	.02	.31	1	–.56	.81	.04	–.65	.01	.35	.14
Knowledge factor	0	.68	.02	–.11	.70	.51	–.10	.23	.24	–.03	–.17	–.56	1	–.52	.13	.72	–.04	–.17	–.01
Perceived risk	.07	–.49	–.06	.13	–.67	–.50	.02	–.60	–.18	.04	.17	.81	–.52	1	0	–.64	.07	.36	.06
Interbrand 100	.22	.22	.01	.08	.08	.17	.07	.06	.11	.08	–.02	.04	.13	0	1	–.01	.04	–.16	.09
Usage (/50)	–.03	.58	0	–.16	.85	.45	–.13	.23	.14	.01	–.18	–.65	.72	–.64	–.01	1	–.07	–.08	.01
Mixed (product/service)	.17	–.03	.03	.01	–.07	.01	.09	.03	–.01	.13	–.05	.01	–.04	.07	.04	–.07	1	–.16	–.03
Service (product/service)	–.09	–.25	–.12	.04	–.18	–.20	–.07	–.61	–.12	–.15	.12	.35	–.17	.36	–.16	–.08	–.16	1	.18
Internet brand	.11	–.01	.08	–.05	0	–.06	–.01	–.18	–.16	–.06	.07	.14	–.01	.06	.09	.01	–.03	.18	1

explanatory variables. These correlations use the full set of brands in our analysis, with the exception of satisfaction, which we calculated using only the 209 brands for which satisfaction is observed.

Our data are aggregate and from multiple sources. This means that we do not observe how the brand perceptions of a *specific* person are translated into his or her specific WOM. However, these multiple sources also mean that different sets of people answered our variables. This separation implies that our analyses are protected from common method variance. In particular, false correlations due to a single measurement system or sampling variation cannot explain our results.

ESTIMATION AND RESULTS

This section describes the empirical model and the estimation results. We also include an analysis of the role of the brand characteristics, the overall importance of the three drivers, a content analysis, and numerous robustness checks.

Empirical Model and Estimation Procedures

The formal model describes a set of brands i = 1, 2, ..., N, each belonging to one of K categories indexed by k. The dependent variables are counts of brand mentions. Counts are typically treated as having a nonnormal distribution; following this practice, we use a negative binomial distribution to model the mentions. Specifically, the probability density of WOM brand mentions from channel m for brand i in category k is expressed by the following equation:

$$y_{ik}^m \sim f_{NegBin}(\gamma_k^m + \beta^m X_{ik}, \alpha^m),$$

where f_{NegBin} is the density of the negative binomial with dispersion parameter α^m, which varies by online and offline channels and mean parameter $\gamma_k^m + \beta^m X_{ik}$. The mean parameter incorporates (1) the vector X_{ik} that includes the variables of interest and controls, (2) the channel-specific linear parameters β^m, and (3) the channel-specific category level effects γ_k^m.

One variable, satisfaction, has a large number of missing values. The reasons are unrelated to the variable's role in WOM, but dropping all observations with missing values would reduce our sample size too severely (by two-thirds). Therefore, we assume a prior for the missing data and use a missing at random assumption to impute values for the missing observations. Specifically, we denote by I the set of observations that are incomplete (i.e., missing values for satisfaction) and by C the set of observations that are complete and let the prior of $i \in I$ follow a normal distribution parameterized by the first two moments of the complete data:

$$X_{ik}^1 \sim f_N[\overline{X}^C, V(X^C)],$$

where the function f_N is the normal density, X_{ik}^1 are the incomplete observations of satisfaction, $\overline{X}^C$ is the mean of the complete data, and $V(X^C)$ is the variance of the complete data. Note that whereas the prior is only based on the complete satisfaction data, the posterior distribution is influenced by the full model likelihood. As a result, and because the observations in I are incomplete only with respect to one variable, the posterior distribution of the imputed data, X_{ik}^1, also depends on the relationship to all the other variables. We note that this Bayesian approach is consistent with the likelihood-based approach Schafer and Graham (2002) suggest and naturally accommodates multiple imputations through the posterior simulation. Web Appendix D (Part D.3; www.marketingpower.com/jmr_webappendix) presents robustness checks against alternative imputation procedures.

To complete the model, we describe the other priors, beginning with the category-level effect. Our brand observations originate from a variety of categories. Different categories may generate more or less WOM on average. Some of this heterogeneity might be explained by the (only) category level variable in the analysis, involvement. The remaining heterogeneity is random from our perspective. Thus, we use a multilevel model, enabling the category level effects to be a function of involvement, an overall average, and a random effect. Specifically, the prior distribution for the kth category-level effect on channel m WOM, γ_k^m is

$$\gamma_k^m \sim f_N(\delta^m Z_k, \sigma_m^2),$$

where δ^m is a row-vector of parameters, σ_m^2 is the variance parameter, and the vector Z_k includes an intercept and the involvement variable. We place priors on the parameters $\theta^m = \{\beta^m, \delta^m, \alpha^m, \sigma_m^2\}$ as follows:

$$\beta^m \sim f_N(\overline{\beta}^m, A^{-1});\ \alpha^m \sim f_{GAM}(a_0, b_0);$$

$$\delta^m | \sigma_m^2 \sim f_N(\overline{\delta}^m, \sigma_m^2 A_\delta^{-1});\ \sigma_m^{-2} \sim f_{\chi^2}(\eta_0, v_0).$$

The distribution f_N is the multivariate normal distribution of same dimension as the mean vector and f_{GAM} is the gamma distribution. We refer to this joint prior on the parameters θ^m as $\pi(\theta^m)$ and note that we use standard values for the prior arguments to generate diffuse priors.

Thus, the complete posterior likelihood, L_m, is proportional to

$$\left[\prod_{i=1}^{n} f_{NegBin}\left(\gamma_k^m + \beta^m X_{ik}, \alpha^m\right)\right]\left\{\prod_{i \in I} f_N\left[\overline{X}^C, V\left(X^C\right)\right]\right\}$$

$$\times\left[\prod_{k=1}^{K} f_N\left(\delta^m Z_k, \sigma_m^2\right)\right]\pi\left(\theta^m\right).$$

We estimate the model using Markov chain Monte Carlo posterior simulation. Web Appendix E (www.marketingpower.com/jmr_webappendix) presents the details related to the estimation.

Results from the Full Model

The full model results appear in Table 5. Next, we organize our discussion of the results by the drivers.

The social driver. We begin our discussion with our focal variable related to the social driver, the level of product differentiation. Recall that our theoretical framework identified this characteristic (in relation to the desire to express uniqueness) and that it was not previously studied in the context of WOM. As the theoretical framework predicted, differentiation (measured by YRBAV's energized differentiation pillar) has a positive and significant effect on WOM both on- and offline. This means that people tend to talk more about differentiated brands than other brands. Notably, as we suggested in the "Theoretical Framework" section, the effect is much stronger in the online setting than in

Table 5
ESTIMATION RESULTS

Variable	Online Posterior Mean	Online (95% Credible Interval)	Offline Posterior Mean	Offline (95% Credible Interval)
Social				
Differentiation	1.78**	(.90, 2.65)	.62**	(.16, 1.12)
Esteem	1.22**	(.66, 1.79)	.52**	(.22, .81)
Middle (premium/value)	.50**	(.31, .69)	.01	(–.09, .10)
Premium (premium/value)	.47**	(.19, .75)	–.07	(–.21, .06)
Relevance	–.26	(–.62, .06)	.29**	(.10, .47)
Visibility	.92**	(.65, 1.17)	.72*	(.53, .91)
Emotional				
Excitement	.71**	(.39, .99)	.44**	(.27, .60)
Satisfaction	4.60*	(–.54, 9.75)	5.59**	(3.21, 8.17)
Satisfaction^2	–3.56**	(–5.25, –1.94)	–3.10**	(–3.93,–2.30)
Functional				
Age	.13	(–.07, .37)	–.17**	(–.29, –.05)
Search	–.30**	(–.56, –.06)	.04	(–.11, .27)
Credence	–.01	(–.37, .37)	–.60**	(–.81, –.39)
Complexity	–.49*	(–.98, .05)	.43**	(.09, .76)
Knowledge factor	.49*	(.33, .65)	.46**	(.36, .56)
Hybrid				
Perceived risk	.91**	(.30, 1.44)	.03	(–.26, .32)
Involvement	–.58	(–2.01, .85)	.13	(–1.01, 1.25)
Controls				
Category average	8.36**	(1.67, 15.37)	–.73	(–5.34, 4.01)
Interbrand top 100	.95**	(.74, 1.17)	.26**	(.14, .39)
Usage	–1.07**	(–2.22, –.13)	–.84**	(–1.36, –.28)
Mixed (product/service)	–.36	(–.99, .34)	.27	(–.15, .62)
Service (product/service)	.54**	(.23, .79)	.62**	(.49, .77)
Internet brand	.31	(–.08, .70)	–.30**	(–.49, –.10)
Dispersion	3.12**	(2.75, 3.51)	8.36**	(7.44, 9.34)

*Significant at the 5% level (i.e., 95% credible interval does not overlap 0).
**Significant at the 10% level (i.e., 90% credible interval does not overlap 0).

offline conversations (1.78 vs. .62). Recall that this might be due to two fundamental differences between online and offline environments. First, in offline interactions, a person has many ways to communicate uniqueness (e.g., by wearing the branded clothes), and brand name-dropping is less necessary for this purpose. Second, online interactions involve broadcasting to a wider audience than most offline communications. As a result, online WOM may involve communicating with many people who are less personally familiar with the communicator, leading to a stronger desire to express personality and especially uniqueness. Differentiation is not the only characteristic for which significant differences exist between online and offline settings. We provide a comprehensive picture of these differences in the "Online Versus Offline" subsection to follow.

The second motive under the social driver is the desire to enhance oneself by associating with high-quality products to demonstrate expertise (measured by esteem) and signal higher status (through premium products). The results for esteem are consistent with these expectations for both online and offline settings, indicating that brands with higher perceived quality are mentioned more often. For premium products, the effect is only significant online. Specifically, we find that relative to value brands, people talk more online about premium and middle-premium brands.

The final social motive, the desire to converse, is measured by visibility and relevance. For visibility, we find the expected positive effect for both channels, indicating that more visible brands are mentioned more often. This result is consistent with Berger and Schwartz (2011) and generalizes their finding to a larger set of brands and categories as well as for both on- and offline channels. For relevance, we find a significant, positive effect offline but an insignificant, negative effect online (for further discussion of such differences, see the subsection "Online Versus Offline").

The emotional driver. The emotional driver includes two characteristics, excitement and satisfaction. We first consider our focal variable for this driver, excitement, which previous research has not explored in the context of WOM. As expected, we find that more exciting brands receive more WOM and that the effect is strongly significant for both online and offline channels. We interpret this result to mean that when consumers are excited about a brand, they are likely to experience emotional arousal that leads them to speak with others.

The role of satisfaction is more complicated. In line with prior research (Anderson 1998; Richins 1983), we expected that at extremely low and high levels of satisfaction, consumers are much more likely to mention brands, leading to a U-shaped effect. To capture this potential shape, we included in the model linear and quadratic terms for satisfaction. However, in both the on- and offline channels, we find a monotonic concave effect. For the observed values of satisfaction (between 55 and 89), we find that as satisfaction increases, WOM decreases. This result means that the data support the greater WOM at low satisfaction levels but do not support greater WOM for high satisfaction levels. It is possible that previous findings about the high WOM levels at high satisfaction levels were due to the exclusion of variables that are related to satisfaction, such as esteem and excitement, which we included in our model. In other words, our analysis studies the role of satisfaction beyond the effect of these variables.

The functional driver. The functional driver relates to the need to obtain and the tendency to provide information. We begin by discussing our focal variable for this driver, complexity, which has not been studied in the context of WOM. The effect of complexity in the offline channel has the expected positive sign and the estimates are statistically significant, but in the online channel, the effect is negative and marginally significant ($p < .1$). In other words, people talk more in the offline world about brands that are more complex, but in an online environment, they talk more about brands that are less complex. Notably, we find a similar pattern (significant and negative offline; insignificant online) for age, indicating that people are more likely to discuss newer brands than older brands offline. Finally, for type of good, we find that for online channels, search goods are mentioned statistically less often than experience goods; yet for offline channels, credence goods are mentioned statistically less often than experience goods.

As for the information supply variables, we find, as expected, significant positive effects for the knowledge factor, meaning that people share more information about brands they are familiar with and knowledgeable about. This tendency is qualitatively the same across the two channels.

We also conducted an analysis in which the coefficients of the model are allowed to differ across the types of good (search, experience, and credence). This moderation analysis, presented in Web Appendix F (www.marketingpower.com/jmr_webappendix), illustrates that our results are relatively robust to such an extension, but at the same time, it also suggests that evaluating such moderation effects could be a fruitful line of research.

The hybrid characteristics. As we discussed previously, two characteristics (perceived risk and involvement) do not fit well into a single driver and thus are considered "hybrid" (i.e., they contain elements of multiple drivers). As we expected, the effect of perceived risk is positive. It is highly significant in the online model but not significant in the offline model. We expected involvement to have a positive effect, but because we measured it at the category level and with only 16 categories, the limited variation did not allow us to estimate the effect adequately. We do not find a significant effect in any of the models.

Controls and dispersion. All our control variables are highly significant; brands in the Interbrand top 100 have higher WOM, brands with higher usage have less WOM, services get more WOM than products, and Internet brands receive less WOM offline. Finally, the dispersion parameter is higher in the offline than the online channel, reflecting the larger dispersion in the number of online mentions. This is a characteristic of the measurement system and modeling approach and not reflective of any actual differences across the two channels.

Online versus offline. Although some variables have a similar coefficient in the online and offline settings (e.g., the coefficients of the knowledge factor are .49 and .46, respectively), others differ meaningfully either in their coefficients or in their significance between the two settings (or both). To present a clear picture of these differences, we discuss them together here. Note that for each variable, we can directly compare the coefficients from the on- and offline regressions because the dependent variables are logged and the independent ones are the same. As a result, in both regressions, the coefficients represent the percentage change in WOM for a unit change in the variable.

We begin with the social driver, for which we find the most dramatic differences. We previously pointed out that differentiation has a much stronger effect online than offline and discussed some possible explanations for these differences. We find a similar difference for esteem, for which the coefficient is significant both online and offline but is more than twice as large online. Furthermore, there is a similar finding with respect to premium. The results for both esteem and premium are consistent with the idea, discussed previously, that people seek to enhance themselves more often online than offline, perhaps due to the lack of nonverbal cues (e.g., clothing brands worn) to help signal status and identity as well as the broadcasting nature of the online medium. In contrast, visibility is similarly strong both online and offline, whereas relevance is significant and positive offline but is negative and not significant online. This difference could be due to the diversity of tastes of the broader online audience, which implies that even brands with lower relevance are still relevant for many people and thus can serve as conversation material; for example, a fan of an indie band may find few fans offline but many online, and thus, the band's low relevance does not suppress online WOM.

The coefficients of the emotional driver are essentially the same across channels, so we next turn to those of the functional driver. Here, the most noteworthy variables are age and complexity. Less complex brands have more WOM online, whereas more complex brands get more WOM offline. A possible explanation for this difference hinges on the advantages of offline conversations in clarifying complex issues, because such conversations are truly interactive and enable quick responses and clarifications. In contrast, online conversations are more likely to be asynchronous (Morris and Ogan 1996) and take more time to respond, clarify, and exchange information. As a result, exploring new or complex features of a brand may be easier offline than online. This same argument can explain the similar result for the age variable.

That said, as we illustrate subsequently (see the "Robustness Checks" subsection), our results are robust, but the estimate of complexity is perhaps least so. Furthermore, some might argue that the lack of effect online (and even its marginally significant opposite effect) is because we did not observe the people who passively browse (i.e., receive but do not post) online (for the differences between WOM generation and consumption, see Yang et al. 2012). By considering both online and offline data together, we can empirically observe the potential effects of this possible shortcoming of typical online data sources.

Results on the Relative Importance of the Three Drivers of WOM

To compare the importance of the variables under the three drivers at the same time, we determine what happens to the fit of the model when we exclude each of these drivers from the analysis. In other words, we examine models with subsets of the variables corresponding to all combinations of the drivers. To compare these submodels, we present the model log marginal likelihoods (LML).

Before proceeding to the results, we highlight two points about this exercise. First, satisfaction requires a missing data model, which induces much greater variation in the LML and, as a result, does not allow us to compare across subsets of drivers. Therefore, we exclude it from this analysis. This exclusion could lead the importance of the emotional driver to be understated. Second, the hybrid characteristics could belong to both the functional and the emotional drivers. Thus, we use submodels with and without the hybrid characteristics to examine the overall role of the three fundamental drivers.

Table 6 presents the results of this analysis (see also Web Appendix G at www.marketingpower.com/jmr_webappendix). The most notable finding here is the difference between online and offline channels. We find that for the online model, the order of importance of the drivers is social, functional, and emotional. Overall, the importance of the social and functional drivers is significantly greater than that of the emotional driver. For the offline model, the order is emotional, functional, and social; the importance of the emotional driver is significantly greater than the other two drivers. In other words, whereas the emotional driver is the most important in offline conversations, the social driver is the major force in online brand mentions. These results portray a nuanced and insightful picture of WOM. One interpretation argues that offline conversations, which typically occur in one-on-one settings, are more personal and intimate and thus allow people to share emotions such as excitement and satisfaction. In contrast, nonverbal signals are not available for online WOM, which usually involves broadcasting to many people (e.g., Twitter) and may be more appropriate for social signaling (e.g., communicating uniqueness).

Table 6

RELATIVE IMPORTANCE OF THE FUNCTIONAL, SOCIAL, AND EMOTIONAL DRIVERS

	Online LML[a]	*Offline LML*
Models with the Hybrid Characteristics		
Social	–8,393.6	–5,745.4
Emotional	–8,455.9	–5,312.0
Functional	–8,439.4	–5,374.4
Social and emotional	–8,376.5	–5,640.2
Functional and emotional	–8,424.1	–5,536.9
Functional and social	–8,392.4	–5,899.7
Models Without the Hybrid Characteristics		
Social	–8,381.8	–5,707.7
Emotional	–8,453.5	–5,316.1
Functional	–8,454.2	–5,408.8
Social and emotional	–8,387.3	–5,573.1
Functional and emotional	–8,412.6	–5,363.8
Functional and social	–8,358.4	–5,867.0

[a]LML with higher (less negative) values, indicating better fit to the data.

Notes: This table indicates that for submodels that contain only one driver, in the online environment, the social driver fits best (LML = –8,394) and functional fits second best (LML = –8,439), whereas in the offline environment, the emotional driver fits best (LML = –5,312) and functional fits second best (LML = –5,374). The same relationship holds for submodels that contain one driver and including the hybrid motives. For submodels containing two drivers, the best models online contain social motives and the best models offline contain emotional motives. This pattern is true for both models with and without the hybrid characteristics.

An alternative explanation of these results is that they are driven primarily by the difference in measurement between online and offline channels. In particular, recall effects may exist in the offline data but not the online data, and it is possible that such effects may lead to greater recall for brands with high levels of emotional characteristics. Although we cannot rule this alternative out, some aspects of the data minimize this possibility. First, the self-reports document only one day, and respondents are requested to keep the diary with them at all times so that we could minimize the lag between occurrence and reporting. Second, the data provider (the Keller Fay Group) ran additional checks in which respondents used smartphones and recording devices to examine whether pure observational behavior differed from the self-reports. They found that the pattern of observed WOM was similar to the self-reported one.

Results on the Connection Between Brand Characteristics and WOM Content

Although our study relates brand characteristics with WOM mentions, it is possible that these characteristics also relate to WOM content. For example, it is possible that exciting brands, such as Arizona Beverage Company, not only receive more WOM but also receive WOM that expresses more excitement about the brand. Although extending our theoretical and empirical framework to address such an issue is beyond the scope of this study, it is worthwhile to observe whether such a content–characteristic connection is likely, using a small-scale test.

For such a test, we focused on (1) three characteristics (excitement, esteem, and differentiation), (2) ten major product categories, and (3) 41 brands that we selected to provide a range of scores above and below average for these three characteristics. Using a commercial text-mining tool (NetBase Solutions's Insight Workbench tool) on online data, an independent coder identified for each category and characteristic a set of words and phrases (called "themes") that could describe this characteristic in the context of the category (e.g., for excitement and cars: "great experience," "popular model," and "head turning"; for excitement and beauty products: "newest beauty obsession"). We then used the text-mining engine to count how often each theme appeared in the brand's WOM mentions as well as the total brand mentions over 365 days from March 2012 to March 2013. Thus, we had a "content score" for each brand and characteristic, calculated by the number of times respondents mentioned this characteristic with respect to this brand, divided by the total mentions.

Using these data, we ran a brand-level (subscripted by i) logistic regression with fixed effects for each of the ten categories (subscripted by k). We estimated the model jointly for all content scores but only allowed the relevant characteristic to affect the content score (e.g., excitement affects the excitement content score). Thus, the model for excitement is

$$\text{Logistic(Excitement Content Score}_{i(k)}) =$$
$$\beta_{0k} + \beta_1\text{Excitement}_{i(k)} + e_{i(k)}.$$

Table 7 presents the results. The coefficients for all three characteristics are positive, and two of three are significant,

Table 7
THE RELATIONSHIPS BETWEEN BRAND CHARACTERISTICS AND CONTENT SCORE

	Brand Characteristic		
Content Score	*Excitement*	*Esteem*	*Differentiation*
Log (excitement)	.29* (.12)		
Log (esteem)		.01 (.13)	
Log (differentiation)			.43* (.21)

*$p < .05$.

suggesting that brand characteristics increase the proportion of brand mentions that involve content that is related to the specific brand characteristic. Although these results are preliminary, they provide encouraging initial support that brand characteristics might have a role that extends beyond a general increase in WOM.

Robustness Checks

In addition to the preceding analyses, we also conducted a range of robustness tests to ensure that our results are not influenced severely by selection biases, multicollinearity, outliers, or the missing data model. We discuss the complete set of analyses in Web Appendix D (www.marketingpower.com/jmr_webappendix) and note a few highlights here.

Selection bias. Our analysis is based on the 600+ most talkable brands. How sensitive are the results to this selection? We can get a sense of the selection issue by decreasing the number of brands to the top 550, 500, 450, and 200. We find that in all but the smallest data set, the order of the three drivers remains the same; that is, the social driver is most important for online WOM, and the emotional driver is most important for offline WOM. Some coefficients change in effect and significance as we decrease the sample size, but overall, the significant effects are relatively robust to sample selection biases. See Web Appendix D, Part D.1 (www.marketingpower.com/jmr_webappendix) for details, including the richness of results across the different sets of brands. For example, age might play a more important role and visibility a less important role in the top 200 brands than in the others.

Multicollinearity. Our analysis of multicollinearity indicates that it has no meaningful impact on our results with respect to either the relative importance of the three drivers or the specific coefficient estimates. See Web Appendix D, Part D.2 (www.marketingpower.com/jmr_webappendix), for details.

Missing data. First, we note that our approach to modeling the missing data is consistent with the recommendation for such situations (Schafer and Graham 2002). Specifically, we use a Bayesian (likelihood-based) approach that imputes the missing data by sampling from the posterior distribution that depends on all the other data. Second, we note that our analysis of the relative importance of the three drivers does not employ the missing data model. Third, to obtain yet another view of robustness, we apply two alternative approaches: case deletion and single conditional imputation. Case deletion uses far fewer observations, and as a result, fewer variables are significant; however, given the smaller sample size, the results are remarkably similar. Conditional imputation ignores the errors in the missing data model but comes close to our full model results. Overall, these robustness checks for the missing data model suggest that our results are not driven primarily by this approach (for details, see Web Appendix D, Part D.3, at www.marketingpower.com/jmr_webappendix).

Outliers. We find relatively minor outlying cases (with absolute standardized residuals < 4). Dropping these cases had no impact on the statistical significance or direction of effects (for details, see Web Appendix D, Part D.4, at www.marketingpower.com/jmr_webappendix).

DISCUSSION

Although brands and WOM are two fundamental marketing concepts, prior research has largely ignored their relationship. Here, we show that they are closely related and demonstrate that brand characteristics play an important role in explaining the level of WOM. Furthermore, these results are consistent with the theoretical framework we present, which posits that the brand characteristics affect WOM through three drivers: social, emotional, and functional.

The results portray a nuanced, intricate picture of the brand–WOM relationship in two aspects. First, all three drivers—social, emotional, and functional—play a role in this relationship. In other words, WOM is not related to only one characteristic (e.g., perceived risk, visibility) or driver. All the brand's facets are involved. Second, the role of brand characteristics differs across the WOM channels. For example, new brands are more talked about offline, but we find no support for this relationship online. In contrast, premium brands have significantly more online brand mentions, whereas we find no support for such a relationship offline. Furthermore, the channels differ in what fundamental drivers are most important to WOM: whereas the order of importance of the three drivers in the online channel is social, functional, and emotional, the order for the offline channel is emotional, functional, and social.

Managerial Implications

Until the early 2000s, WOM was largely considered a side effect of marketing activity. Today, marketers are trying to develop a systematic approach to manage it.[6] Our work can assist in this task. As we demonstrate in the following four points, this research can provide practitioners with tools in planning, measuring, and managing not only their WOM initiatives but also their branding practices and marketing mix as a whole.

Connecting brand characteristics and WOM. Marketers are interested in creating talkable brands ("Creating Talkable Brands" was the title of WOMMA's annual summit in 2012). Our findings can assist them in identifying the brand characteristics that can accomplish this. A brand manager who wants high WOM can now evaluate which characteristics to use to design WOM into a brand. Consider the case of visibility. A firm that developed a new type of digital music player for cars may have a technological option to embed this player deep in the dashboard or make it a more visible component of the interior. Because visibility enhances WOM and because our model can project the

[6]In this context, for example, practitioners debate whether WOM and advertising are complementary to or substitute for each other (for a review, see Armelini and Villanueva 2010).

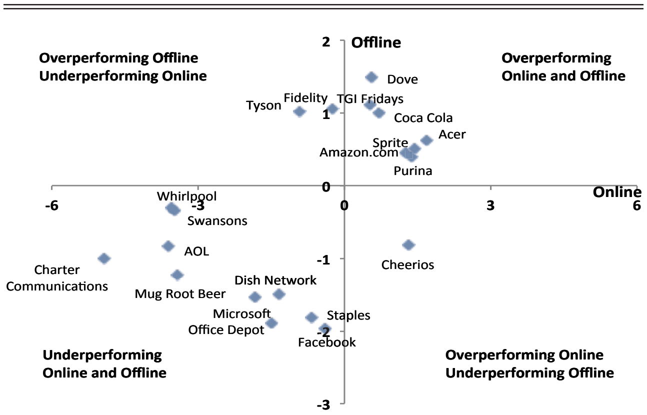
magnitude of the effect, a brand manager may be able to weigh the total costs and benefits of the design choice. The "Intel Inside" campaign of 1999 did something similar: it increased the visibility of the microprocessor and contributed to the firm's WOM (Intel is on our list of 700 brands).

To assist managers in such an evaluation task, we created a model-based Descriptive Decision Support System (DDSS) in Microsoft Excel (Power and Sharda 2009). To use it, managers would need to conduct a survey among consumers in their target market to measure the brand characteristics and enter these into the DDSS to obtain the expected level of WOM.

This method can be also used as a diagnostic tool for one dimension of brand health, a diagnosis that is of increasing importance to brand managers (Berg, Matthews, and O'Hare 2007). Specifically, by comparing the expected level of WOM to the actual level, it is possible to determine whether the actual level is above or below the expected WOM and test whether the brand lives up to its WOM potential. As Figure 3 indicates, on the one hand, Dove, T.G.I. Friday's, and Coca-Cola do exceptionally well offline (i.e., there is a large positive gap between actual and expected WOM). On the other hand, AOL, Charter Communications, and Mug Root Beer do poorly both offline and online compared with what we would expect on the basis of their brand characteristics. Notably, brands such as Facebook, Staples, and Cheerios meet or exceed the expectations online but underperform offline. Managerially, this could call for more efforts to exploit these brands' WOM potential in the offline environment (which is still the highest-volume WOM channel). Note that the focus here is on the performance relative to expectations rather than on absolute values. Low levels of WOM might not necessarily indicate a problem; some brands, given their characteristics, cannot expect high levels of WOM. This is especially evident in the case of categories such as financial products. Indeed, awareness of

Figure 3

ACTUAL VERSUS PREDICTED PERFORMANCE FOR TOP 2% OF OVERPERFORMING AND UNDERPERFORMING BRANDS



Notes: We measured brands' WOM performance using the log(observed WOM) minus the expected log(WOM) for the brand based on our model. The scales are differences in logs (of WOM). Note that in these calculations, we incorporate the category-level random effects but not those of the brand level.

their WOM potential should shape how brands set marketing communications, objectives, and strategies.

The differences between online and offline WOM. We already know that whereas some brands (e.g., Google, Audi, eBay) have a strong and active online WOM presence, others (e.g., Coca-Cola, Wal-Mart, Sony) perform well offline. Our results show that this might be due to differences in how their characteristics affect WOM in the two channels. These findings are relevant for managers in at least three aspects. First, they suggest that copying methods that lead to success in one medium of communications does not guarantee success in the other. For example, sending samples of home products to bloggers might not be effective in stimulating them to spread WOM about them.

Second, the findings indicate that following the trend of relying on measures of online WOM (e.g., NM Incite, Brandwatch, Netbase, Radian6) to assess success in stimulating a conversation about a brand might not be a good idea. Our findings imply that such measures might not be relevant for some managers. Notably, we recently heard a manager of several well-known household brands express frustration because she believes that most of the WOM for her brands comes from offline channels, and yet her performance is measured using online monitoring tools. Our findings can help to avoid such misaligned incentives. Furthermore, it is worth pointing out that most WOM volume is still offline (Keller and Fay 2012).

Third, our results call for caution in generalizing findings from academic studies, because many of these studies were conducted on online channels—for example, the carryover of WOM referrals in social networking sites (Trusov, Bucklin, and Pauwels 2009), the impact of WOM on television viewing (Godes and Mayzlin 2004), and the tone and style of WOM in blogs (Kozinetz et al. 2010). These findings are valid for the channels in which they were measured, but generalizing them to offline channels should be done carefully.

A novel benefit of product differentiation. Product differentiation is a key concept in marketing strategy. We advise brand managers to determine both points of parity and points of differentiation. To justify the costs of creating differentiation, scholars have attempted to explore their benefits and discuss conditions under which differentiation should be pursued (Bronnenberg 2008; Dubé 2004; Schmalensee 1982). Our work contributes to the discussion by identifying a novel benefit of product differentiation beyond brand perception and competitive positioning. We find that differentiated brands have higher WOM and that this effect is one of the largest among the variables that we study both online and offline. Our findings could have dramatic implications for managers; for example, it is possible that even in cases in which differentiation does not have a direct competitive benefit, its indirect effect through WOM on sales can justify investment in creating differentiation.

Justifying investment in brands. The large investment in branding has driven researchers and practitioners to measure the financial outcomes of branding activities and translate brand equity measures into performance metrics such as profits, customer acquisition, and retention (Leone et al. 2006; Stahl et al. 2012). It is argued that strong brand association leads to enhanced identification and loyalty, which then translate to higher acquisition and retention rates. Our findings suggest an additional merit of branding: brand equity has a direct and strong impact on the ability to generate WOM. The four pillars Y&R uses to measure brand equity as well as the Interbrand top 100 variable play significant roles in explaining WOM. This additional merit enriches the set of aspects that should be considered for measuring the impact of brand equity and aids efforts to reach a more comprehensive understanding of the return on branding.

LIMITATIONS AND FURTHER RESEARCH

Of course, our study has its limitations. Because we use cross-sectional, observational data, we cannot empirically establish a sense of causality. What we can do is examine both whether the expected effect of each brand characteristic is present after controlling for all other factors and which effects are most important. As yet, no study has considered such joint effects for brands and their characteristics on WOM. Another limitation of our data is that they contain only the most talked-about brands. As a result, our findings may not be applicable to brands with relatively little WOM. Although we have provided some evidence on the robustness of our findings to the selected sample, our data cannot completely rule out this possibility.

In addition, we relied on measures of aggregate brand mentions rather than ones disaggregated by source. Although this aggregation enables us to examine WOM across many different brands, categories, and channels, a clearer picture might emerge with regard to mechanisms underlying specific channel effects through more disaggregate data. Further research could use finer-grained data to study these and other, more nuanced questions. Along these lines, this work lays the ground for further research in several directions, outlined in the following subsections.

Channel Effects

In this article, we focused on the relationship between brand characteristics and WOM and presented results from online and offline channels as a way to test the generalizability of our findings. However, channel effects convey many opportunities for further research. More channels can be explored beyond the offline–online dichotomy. Online channels (e.g., e-mail, Twitter, blogs, user groups) are different and can show varied patterns of WOM. Gaining a better understanding of WOM's dynamics across channels can help shape strategies for generating WOM, responding to WOM issues, and identifying leading and lagging indicators of WOM.

Valence and Content

In this study, we counted the overall mentions of WOM, regardless of other WOM dimensions such as content and valence. However, brand characteristics may play a role that goes beyond the mere number of mentions. For valence, although most WOM is neutral or positive (Keller and Fay 2012), negative WOM is unique because of its possible impact on adoption and purchase behaviors. Previous studies have explored the implications and contexts of negative WOM (e.g., Moldovan, Goldenberg, and Chattopadhyay 2011); however, the antecedents of negative WOM have received little research attention. As for the content, we present some preliminary evidence indicating that brand characteristics are also relevant for WOM content, but further research can shed additional light on characteristics–content relationships.

Individual-Level Insights

This study examines WOM behaviors at the brand level, using aggregate measures of WOM. As a result, we cannot make claims regarding the WOM behaviors of individual people. For example, do the online–offline variances we documented result from the same people talking about different brands in different channels, or do different groups with different interests prefer specific channels? Answering such questions requires a significantly different and new data set that tracks the WOM process at the individual level. To our knowledge, no such data set exists, but building one could greatly enhance understanding of WOM behaviors at the individual level.

Moderators of the Brand Characteristics–WOM Relationship

Although this study focuses on the main effects of brand characteristics, we found in our robustness checks that the variables related to product type (search, experience, and credence) may play a more complex role that includes moderation. Future studies could explore such moderating roles.

The goal of the current research is to shed more light on the intricate relationships between brands and WOM. We believe that such an understanding can benefit research on both WOM and brands. The research on WOM will benefit from understanding the antecedents of WOM, its patterns, and channel interactions. Branding research will benefit because WOM is an indicator for market response. This article takes the first step in linking these two literature streams and providing insight into fruitful areas of further research.

REFERENCES

Aaker, Jennifer L. (1997), "Dimensions of Brand Personality," *Journal of Marketing Research*, 34 (August), 347–56.

Amblee, Naveen and Tung Bui (2008), "Can Brand Reputation Improve the Odds of Being Reviewed On-Line?" *International Journal of Electronic Commerce*, 12 (3), 11–28.

Anand, Bharat N. and Ron Shachar (2011), "Advertising, the Matchmaker," *RAND Journal of Economics*, 42 (2), 205–245.

Anderson, Eugene (1998), "Customer Satisfaction and Word of Mouth," *Journal of Service Research*, 1 (1), 5–17.

Armelini, Guillermo and Julian Villanueva (2010), *Marketing Expenditures and Word-of-Mouth Communication: Complements or Substitutes*. Hanover, MA: Now Publishers Inc.

Berg, Julie Dexter, John M. Matthews, and Constance M. O'Hare (2007), "Measuring Brand Health to Improve Top-Line Growth," *Sloan Management Review*, 49 (1), 61–68.

Berger, Jonah and Chip Heath (2007), "Where Consumers Diverge from Others: Identity Signaling and Product Domains," *Journal of Consumer Research*, 34 (2), 121–34.

——— and Katherine L. Milkman (2012), "What Makes Online Content Viral?" *Journal of Marketing Research*, 49 (April), 192–205.

——— and Eric Schwartz (2011), "What Drives Immediate and Ongoing Word of Mouth?" *Journal of Marketing Research*, 48 (October), 869–80.

Bronnenberg, Bart J. (2008), "Brand Competition in CPG Industries: Sustaining Large Local Advantages with Little Product Differentiation," *Quantitative Marketing and Economics*, 6 (1), 79–107.

Che, Hai, Nicholas H. Lurie, and Allen M. Weiss (2011), "Roles, Incentives, and Contribution Behavior in Online Communities," working paper, University of Southern California.

Cheema, Amar and Andrew M. Kaikati (2010), "The Effect of Need for Uniqueness on Word of Mouth," *Journal of Marketing Research*, 47 (June), 553–63.

Chevalier, Judith A. and Dina Mayzlin (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research*, 43 (August), 345–54.

Dichter, Ernest (1966), "How Word-of-Mouth Advertising Works," *Harvard Business Review*, 16 (November/December), 147–66.

Dubé, Jean-Pierre (2004), "Multiple Discreteness and Product Differentiation: Demand for Carbonated Soft Drinks," *Marketing Science*, 23 (1), 66–81.

Fornell, Claes, Michael D. Johnson, Eugene W. Anderson, Jaesung Cha, and Barbara Everitt Bryant (1996), "The American Customer Satisfaction Index: Nature, Purpose, and Findings," *Journal of Marketing*, 60 (October), 7–18.

Godes, David and Dina Mayzlin (2004), "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science*, 23 (4), 545–60.

Goldenberg, Jacob, Donald Lehmann, Daniella Shidlovski, and Michal Master Barak (2006), "The Role of Expert Versus Social Opinion Leader in New Product Adoption," MSI Working Paper No. 06-124.

———, Barak Libai, Sarit Moldovan, and Eitan Muller (2007), "The NPV of Bad News," *International Journal of Research in Marketing*, 24 (3), 186–200.

Han, Young Jee, Joseph C. Nunes, and Xavier Drèze (2010), "Signaling Status with Luxury Goods: The Role of Brand Prominence," *Journal of Marketing*, 74 (July), 15–30.

Heath, Chip, Chris Bell, and Emily Sternberg (2001), "Emotional Selection in Memes: The Case of Urban Legends," *Journal of Personality and Social Psychology*, 81 (6), 1028–41.

Ho, Jason Y.C. and Melanie Dempsey (2010), "Viral Marketing: Motivations to Forward Online Content," *Journal of Business Research*, 63 (9/10), 1000–1006.

Hoffman, Dona L. and Thomas P. Novak (1996), "Marketing in Hypermedia Computer-Mediated Environments: Conceptual Foundations," *Journal of Marketing*, 60 (July), 50–68.

Illouz, Eva (2007), *Cold Intimacies: The Making of Emotional Capitalism*. Cambridge, UK: Polity Press.

Katona, Zsolt, Peter Zubcsek, and Miklos Sarvary (2011), "Network Effects and Personal Influences: Diffusion of an Online Social Network," *Journal of Marketing Research*, 48 (June), 425–43.

Keller, Ed (2007), "Unleashing the Power of Word of Mouth: Creating Brand Advocacy to Drive Growth," *Journal of Advertising Research*, 47 (4), 448–52.

——— and Brad Fay (2012), *The Face-to-Face Book: Why Real Relationships Rule in a Digital Marketplace*. New York: The Free Press.

Kozinets, Robert V., Kristine De Valck, Andrea C. Wojnicki, and Sarah J.S. Wilner (2010), "Networked Narratives: Understanding Word-of-Mouth Marketing in Online Communities," *Journal of Marketing*, 74 (March), 71–89.

Laband, David N. (1986), "Advertising as Information: An Empirical Note," *The Review of Economics and Statistics*, 68 (3), 517–52.

Leone, Robert P., Vithala R. Rao, Kevin L. Keller, Anita M. Luo, Leigh McAlister, and Rajendra Srivastava (2006), "Linking Brand Equity to Customer Equity," *Journal of Service Research*, 9 (2), 125–38.

Lutz, Richard J. and Patrick J. Reilly (1974), "An Exploration of the Effect of Perceived Social and Performance Risk on Consumer Information Acquisition," in *Advances in Consumer Research*, Vol. 1, Scott Ward and Peter Wright, eds. Ann Arbor, MI: Association for Consumer Research, 393–405.

Moldovan, Sarit, Jacob Goldenberg, and Amitava Chattopadhyay (2011), "The Different Roles of Product Originality and Usefulness in Generating Word of Mouth," *International Journal of Research in Marketing*, 28 (2), 109–119.

Moore, Gary C. and Izak Benbasat (1991), "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation," *Information Systems Research*, 2 (3), 192–222.

Morris, Merrill and Christine Ogan (1996), "The Internet as Mass Medium," *Journal of Computer-Mediated Communication*, 1 (4), 39–50.

Mudambi, Susan M. and David Schuff (2010), "What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.com," *MIS Quarterly*, 34 (1), 185–200.

Nardi, Bonnie A., Diane J. Schiano, Michelle Gumbrecht, and Luke Swartz (2004), "Why We Blog," *Communications of the ACM*, 47 (12), 41–46.

Nelson, Phillip (1974), "Advertising as Information," *Journal of Political Economy*, 82 (4), 729–54.

Ostlund, Lyman E. (1974), "Perceived Innovation Attributes as Predictors of Innovativeness," *Journal of Consumer Research*, 1 (2), 23–29.

Parasuraman, A., Valarie A. Zeithaml, and Leonard L. Berry (1985), "A Conceptual Model of Service Quality and Its Implications for Future Research," *Journal of Marketing*, 49 (October), 41–50.

Peres, Renana, Eitan Muller, and Vijay Mahajan (2010), "Innovation Diffusion and New Product Growth: Critical Review and Research Directions," *International Journal of Research in Marketing*, 27 (2), 91–106.

Peters, Kim and Yoshihisab Kashima (2007), "From Social Talk to Social Action: Shaping the Social Triad with Emotion Sharing," *Journal of Personality and Social Psychology*, 93 (5), 780–97.

Power, Daniel J. and Ramesh Sharda (2009), "Decision Support Systems," in *Springer Handbook of Automation*, Shimon Y. Nof, ed. Berlin: Springer, 1539–48.

Ratchford, Brian T. (1987), "New Insights About the FCB Grid," *Journal of Advertising Research*, 27 (4), 24–38.

Richins, Marsha L. (1983), "Negative Word-of-Mouth by Dissatisfied Consumers: A Pilot Study," *Journal of Marketing*, 47 (January), 68–78.

Roberts, Kevin (2004), *Lovemarks: The Future Beyond Brands*. New York: PowerHouse Books.

Rogers, Everett M. (1995), *The Diffusion of Innovations*. New York: The Free Press.

Rosen, Emanuel (2002), *Anatomy of Buzz*. New York: Doubleday.

Rubin, Rebecca B., Elizabeth M. Perese, and Carole A. Barbato (1988), "Conceptualization and Measurement of Interpersonal Communication Motives," *Human Communication Research*, 14 (4), 602–628.

Schafer, Joseph L. and John W. Graham (2002), "Missing Data: Our View of the State of the Art," *Psychological Methods*, 7 (2), 147–77.

Schmalensee, Richard (1982), "Product Differentiation Advantages of Pioneering Brands," *The American Economic Review*, 72 (3), 349–65.

Speier, Cheri and Viswanath Venkatesh (2002), "The Hidden Minefields in the Adoption of Sales Force Automation Technologies," *Journal of Marketing*, 66 (July), 98–111.

Stahl, Florian, Mark Heitmann, Donald R. Lehmann, and Scott A. Neslin (2012), "The Impact of Brand Equity on Customer Acquisition, Retention, and Profit Margin," *Journal of Marketing*, 76 (July), 44–63.

Sundaram, D.S., Kaushik Mitra, and Cynthia Webster (1998), "Word-of-Mouth Communications: A Motivational Analysis," in *Advances in Consumer Research*, Vol. 25, Joseph W. Alba and J. Wesley Hutchinson, eds. Provo, UT: Association for Consumer Research, 527–31.

——— and Cynthia Webster (1999), "The Role of Brand Familiarity on the Impact of Word-of-Mouth Communication on Brand Evaluations," in *Advances in Consumer Research*, Vol. 26, Eric J. Arnould and Linda M. Scott, eds. Provo, UT: Association for Consumer Research, 664–70.

Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site," *Journal of Marketing*, 73 (September), 90–102.

Veblen, Thorstein (1994[1899]), *The Theory of the Leisure Class*. New York: Penguin. First published 1899 by Macmillan Publishers.

Walther, Joseph B. (1996), "Computer-Mediated Communication: Impersonal, Interpersonal, and Hyperpersonal Interaction," *Communication Research*, 23 (3), 3–43.

Wojnicki, Andrea and David Godes (2011), "Signaling Success: Strategically Positive Word of Mouth," working paper, Harvard Business School.

WOMMA (2011), "WOMMA Summit 2012 Announced—Focuses on Creating Talkable Brands," press release, (September 29), (accessed May 14, 2013), [available at http://finance.yahoo.com/news/WOMMA-Summit-2011-Agenda-iw-2222982791.html].

Yang, Sha, Mantian Hu, Russell S. Winer, Henry Assael, and Xiaohong Chen (2012), "An Empirical Study of Word-of-Mouth Generation and Consumption," *Marketing Science*, 31 (6), 952–63.

Zaichkowsky, Judith L. (1985), "Measuring the Involvement Construct," *Journal of Consumer Research*, 12 (3), 341–52.