On brands and word-of-mouth

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Abstract:

Brands and word-of-mouth are cornerstones of marketing. Yet, their relationship has received relatively little attention.

This study aims to enhance our understanding of brand characteristics as antecedents of WOM by executing a comprehensive empirical analysis. For this purpose, we constructed a unique data set on online and offline WOM and characteristics for over 600 of the most talked-about brands.

To guide this empirical analysis we present a theoretical framework whose fundamentals are consumers and what stimulates them to engage in WOM. It argues that consumers spread the word on brands as a result of three drivers: social, emotional, and functional. Through these drivers we identify a set of thirteen brand characteristics that play a role in stimulating WOM – three of them have not been studied as WOM antecedents: level of differentiation, excitement and complexity.

We find that many of the brand characteristics we identified, including the three that were studied for the first time, play an important role in WOM. We also find that while the social and functional drivers are the most important for online WOM, the emotional driver is the most important for offline WOM. These results portray an interesting picture of WOM and have meaningful managerial implications for brand management and investment in WOM campaigns.

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

Introduction

Do differentiated brands get more or less word-of-mouth than others? Does the level of differentiation even matter when it comes to word-of-mouth? And how about the degree of a brand's complexity, or its level of excitement? We do not know. More broadly, although brands and word-of-mouth are cornerstones of marketing, their relationship has received relatively little attention. While 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 and Katona, Zubcsek and Sarvary 2011) of word-of-mouth (WOM hereafter), our understanding of brand characteristics as antecedents to WOM is surprisingly limited. That is, the two broad literatures 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 marketing practitioners for a variety of reasons such as creating talkable brands and maximizing the impact of branding activities (Rosen 2002, WOMMA http://womma.org/talkablebrands/).

This study aims to enhance our understanding of brand characteristics as antecedents of WOM by executing a comprehensive empirical analysis that examines the brand characteristics-WOM relationships for a large number of brands. Specifically, we collected data on the 697 most talked-about national US brands. These brands come from 16 different categories (e.g., food, media and entertainment, cars, financial services, sports), and include product and service brands, corporate brands and product-specific brands. The analysis is comprehensive not only due to the large number of brands. While existing research generally relies on either online or offline measures of WOM, we incorporate both. Furthermore, while previous scholars who were interested in the antecedents of WOM focused on only one or two brand characteristics, we evaluate the role of a broad set of brand characteristics.

To guide this empirical analysis we start by developing a theoretical framework that identifies brand characteristics relevant for WOM. This framework, whose fundamentals are consumers and what stimulates them to engage in WOM, argues that consumers spread the word on brands as a result of three drivers: social, emotional, and functional. The social driver relates to social signaling: expressing uniqueness, self-enhancement, and a desire to socialize; the emotional driver is related to emotion sharing; the functional driver is related to the need to obtain information, and the tendency to provide information. Understanding these drivers and the needs associated with them help us to identify specific brand characteristics that play a role in stimulating WOM. Consider for example the social driver and specifically the need to express uniqueness: it is easier to signal one's uniqueness through a highly differentiated brand than an undifferentiated brand. As a result, we argue that a brand with a higher degree of differentiation is likely to have greater WOM. Interestingly, the potential role of differentiation on WOM was not studied so far. Two additional characteristics that are novel and unique to our study are brand’s level of excitement and its complexity.

Another layer of our analysis relates to the heterogeneity of WOM across channels of communications. Specifically, the purpose and nature of WOM differ between offline conversations and online brand mentions. While offline communication is usually one-to-one, and carries also non-verbal clues, online communication is generally written and usually one-to-many, that is, read by a large number of people. Accordingly, we expect that the impact of the drivers would 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 national US brands. For each of these brands we compiled data on offline and online WOM and, following our theoretical framework, on their characteristics. The data on brand characteristics come from (a) a survey we conducted on a representative sample of the US containing 4,769 respondents (on characteristics such as complexity and excitement) and (b) the proprietary Young and Rubicam data based on their Brand Asset Valuator panel (on characteristics such as differentiation). The data on the offline WOM come from the Keller Fay group (Keller 2007). It includes a weekly measure of the offline WOM (i.e., face-to-face and phone conversations) for over 1000 brands mentioned from January 2007 to August 2010. The online data come from the Buzzmetrics tool of Nielsen-McKinsey Incite, and includes 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 one of the drivers identified in our theoretical framework (social, emotional, and functional) is relevant and significant in this process. Furthermore, each one of the characteristics introduced for the first time in the context of WOM by our theoretical framework (differentiation, complexity and excitement) is found to have a significant relationship with WOM. For example, we find that brands that are highly differentiated from others (and thus enable individuals to express their uniqueness) have, as expected, more WOM. Interestingly, 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 characteristics level. In some cases, characteristics have a significant effect in one setting but not in the other (e.g. age of brand). These differences at the level of the brand characteristic are indicative of interesting differences with respect to the importance of the three overall drivers. We find that while the social and functional drivers are the most important for online WOM, the emotional driver is the most important for offline WOM. These results portray an interesting picture of WOM. Offline conversations, which are mostly in one-on-one settings, are more personal and intimate by nature and thus allow people to share emotions such as excitement and satisfaction. Online WOM, which usually involves "broadcasting" to many people (e.g. twitter), is more appropriate for social signaling (e.g., 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 instance, 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 them is that the brand has not lived up to its WOM potential. Thus, such evidence might suggest re-examining the WOM strategy used by the firm. In order to assist managers in diagnosing their brands' WOM performance we created a model-based Descriptive Decision Support System (DDSS) in Excel (Power and Sharda 2009).

Theoretical framework

This section introduces our theoretical framework, which is then used to identify brand characteristics relevant for WOM. We start from the most fundamental element – consumers and what stimulates them to engage in WOM. Building on previous research, we argue that consumers spread the word on brands for three fundamental purposes: social, emotional, and functional. In brief: the main social driver is to send signals to others as to one's expertise, uniqueness or social status; the emotional driver is to share positive or negative feelings about brands in order to balance emotional arousal; and the functional driver is to provide and supply information. While there are possibly additional drivers, based on previous research we consider these three to be the major ones.

We use the term “theoretical framework” rather than “theory” or “model” to adequately reflect its role in this study. The main contribution of this study 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, and suggesting possible interpretation for the results.

In the rest of this section we discuss in more detail the relevant literature, and the three fundamental drivers. Furthermore, for each driver we identify the relevant brand characteristics. For clarity, in the text below, brand characteristics that are included in our model are underlined.

The Social Driver

Self enhancement: An interesting social motive to engage in WOM is self-enhancement. Wojnicki and Godes (2011) show that consumers strategically use WOM in order to signal or enhance their perceived expertise. To achieve this purpose, positive WOM is more effective than negative, since 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 are consumers 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 (Hans, Nunes and Dreze 2010), where luxury goods signal a high social status (Veblen 1899). We suggest that individuals 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 demonstrated that consumers use consumption and possessions to express their uniqueness or their group identity (e.g. Berger and Heath 2007), but surprisingly ignored the possibility to employ WOM for this purpose.[1] We suggest that consumers could express their uniqueness also by talking about brands. Further, we suggest that some brands would be 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. As a result, we hypothesize that the higher the degree of differentiation of a brand, 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 et al 1988) can lead to WOM. Berger and Schwartz (2011) demonstrate empirically that brand's visibility eases individuals' 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 a social conversation is whether it is relevant in the lives of many people. For example, an indie band is less likely

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

to be a better conversation material than a mainstream one.[2] Thus, we expect that as brands become relevant to more people they are more likely to allow conversation.

The Emotional Driver

Consuming a brand or thinking about it can invoke emotions that individuals might like to share with others (Heath, Bell, and Sternberg 2001; Nardi et al 2004; Peters and Kashima 2007) in order to express or ease emotional arousal (Berger and Milkman 2012). Previous studies 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.

Interestingly, the role of brand's excitement (one of the five brand personality traits introduced in Aaker 1997) was overlooked in this context. However, excitement is certainly a stimulating emotion that can be eased via conversation, and thus it is reasonable to expect that the higher the brand's excitement, the more likely are individuals to engage in WOM on it.

The Functional Driver

In many conversations individuals exchange useful and practical information (e.g., what is the best route from New York to New Haven) and often brands are the subject of that information exchange. In any such exchange there is a person who needs the information and one that 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 since the uncertainty associated with them is higher (see Peres, Muller and Mahajan 2010 for a review). Furthermore, existing evidence indirectly suggests that WOM decreases over

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

the life of a brand (Godes and Mayzlin 2004). Accordingly, we include the age of the brand and directly test whether WOM is higher for newer brands.

While previous studies have focused on the newness of the brand as a source of uncertainty, we suggest that another characteristic (ignored by previous studies on WOM) might be in play – the brand's complexity in the sense of difficulty to obtain and comprehend information on it. We hypothesize that the higher the complexity, the higher the WOM on the brand. Notice that while the relationship between this characteristic and WOM was ignored, it was discussed in the context of diffusion of innovation (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). WOM can be useful for exploring intangible attributes of experience goods (e.g., ambience in a restaurant) and 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 identified individuals' motives to provide information (e.g. altruism and reciprocity). In order to be able to provide information and to engage in a conversation about a brand, it has to be familiar to the individual. Thus, we hypothesize that a higher level of familiarity (Sundaram and Webster 1999) or knowledge about the brand will be associated with more WOM.

Hybrid Characteristics

Two additional brand characteristics discussed by 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 nicely into only one of the drivers. Involvement can be both functional and emotional – functional since individuals are likely to seek more information on high involvement products and emotional since some commonly used scales of involvement use 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 emotional drivers. Rogers (1995) discussed three aspects of risk – the actual performance of the brand, the extra expenses that might be incurred, and the social embarrassment that might be caused by the brand. While each of these risks might motivate consumers to seek information in order to resolve them, they might also induce anxiety that consumers may want to express. In fact, Sundaram, Mitra and Webster (1998) focused on this emotional aspect of risk.

As will be discussed later, 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--along with the associated brand characteristics. We propose that these brand characteristics affect the level of WOM. In the following section, we describe the measures and data collection procedures we use for these brand characteristics and for WOM on both online and offline channels.

Online versus offline

So far we have discussed WOM without distinguishing between offline conversations and online mentions. However, it is quite 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 one "broadcasts" a message to many (e.g. *Facebook or Twitter*), offline conversations are frequently in a personal one-on-one setting (Hoffman and Novak 1996; Morris and Ogan 1996). Second, in offline meetings (especially in face-to-face ones) the communication extends beyond the words. For example, we can use tone, facial expressions, and body language. Third, offline interactions are more interactive ("synchronous" in communications terminology), in the sense that the other conversation parties are expected to respond and usually immediately (Morris and Ogan 1996). In contrast, online channels such as blogs, user forums and twitter are in many cases one directional and asynchronous, with no immediate (if any) response.

As a result of such differences, it is reasonable to expect that the role of the drivers and characteristics would differ between the two mediums of communication. Consider the three characteristics that were not studied as WOM antecedent so far: differentiation, excitement, and complexity. As discussed above, differentiation enables the individual to express her uniqueness. Since in most online interactions (i) the format is of "broadcasting" to many (Morris and Ogan 1996), and (ii) interactions are more likely to take place with unfamiliar individuals (Walther 1996), the tendency to express aspects of oneself in general, and specifically uniqueness, should be higher. Furthermore, the ability to express uniqueness non-verbally is higher in the offline setting than in online interactions (Illouz, 2007, chap 3). For example, when the individual wears a shirt of a highly differentiated brand, she does not need to mention it in the conversation. As a result of these two factors, one might expect differentiation to play a more important role in online versus offline interactions.

On the other hand, 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. Also, when excited, people might be seeking the 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, and the ability to ask and answer questions, which assists individuals to comprehend complex brands. This stands in contrast to online communications which are not only asynchronous but also are sometimes limited in length (e.g. Twitter, user forums) and thus limit thorough discussion.

While (i) we do not offer a clear theory on this matter and (ii) the focus of our study is not on understanding these differences, per se, we will study the effect of brand characteristics on online and offline WOM separately in order to avoid mis-specification of the model, and provide some initial empirical insights on this issue.

Data

In order to study the role of brand characteristics in stimulating WOM we have used several sources to build a comprehensive data set, which contains information on WOM as well as brand characteristics for 697 major US national brands spanning 16 broad product categories (the full list of brands and categories as well as its construction is given in the Web Appendix (part 1).[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 heterogeneity of brands in the list is very high including both corporate and product brands. These include consumer brands such as *Coca Cola* and *Dove*, services such as *Expedia*, *Charles Schwab* and *Burger King*, sports-teams such as the *Boston Celtics*, and television shows such as *CSI*. For each brand, we collected data on WOM, brand characteristics, and relevant control variables. Figure 2 describes the complete set of data sources we use. They are described in detail in the next subsections.

Word-of-Mouth Data

Word-of-mouth can be distributed and consumed through a variety of channels, which are grouped here into two main categories – offline channels such as face to face and telephone conversations, and online channels such as blogs, emails, 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 of these main channels and conduct our analysis on these two categories separately.

[3] This list was compiled based on our WOM data to contain the most talked about brands in the US between the years 2007-2010.

1. *Offline word-of-mouth* – The TalkTrack project of the Keller and Fay group is the most accepted measure of offline WOM by the industry (for example, by the word-of-mouth association, WOMMA). This is a diary-style survey on a representative sample of the US 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 had 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 aggregate the number of mentions between January 2007 and August 2010 and include both phone 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*.

2. *Online word-of-mouth* – The source for the online WOM data is the Nielsen McKinsey Incite tool, (formerly BuzzMetrics). This is a search engine that has conducted daily searches through blogs, discussion groups, and microblogs since July of 2008 and for each of these sources processes all available posts.[4] As in the case of the offline data, we have 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 highest number (14,579,172) is Google.

Table 1 displays the top 10 brands online and offline. Notice 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.

The way we obtain the brand mentions is different between the two channels. In the offline data we use a sample of individuals, while in the online data we use a sample of posts. This means that for the online data (like previous studies that used online WOM data) we do not observe the receiving side of the

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

communication but rather only the "sender". For some purposes this would mean a selection bias. For instance, for measuring individual level propensities to engage in WOM, our sample has problems. However, for our purposes – i.e., to measure aggregate brand mentions online – this sample is appropriate. Another difference between these two datasets could be 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 differences in people rather than the channel per se. After presenting our results, we discuss some ways future research may leverage more refined measures to provide a more disaggregate picture of WOM behaviors.

Brand Characteristics

In order to operationalize the brand characteristic variables identified in Figure 1, we use existing measurement scales (e.g. Aaker's brand personality) whenever possible. In order to collect the data, we conducted a large-scale original data collection on the top of a number of existing public and proprietary databases. We combine these sources as described in Figure 2.

The first source is the proprietary database of *Young and Rubicam* called "Brand Asset Valuator" (YRBAV hereafter). It measures brand equity on four perceived dimensions (referred to as "pillars" by *Y&R*): Energized-Differentiation, Relevance, Esteem, and Knowledge. This dataset is constructed 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. Based on this survey *Y&R* build the four "pillars" for each brand.

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

[5] Decipher, Inc., a California-based company that specializes in developing and managing large-scale surveys. The questionnaire starts with screening questions about the level of familiarity with the category and the brands. Then, the system chooses several brands with which the respondent indicated familiarity, and asks 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. An annotated version of this complex questionnaire is described in the Web Appendix (part 2).

In addition, we used several other secondary sources. First, we used Interbrand data on the brands that were ranked in the top 100 places of their list over the last few years. Second, we use 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.

The rest of this subsection describes our variables, scales, and measures in detail – their summary statistics appear in Table 3.

1. **Age** – We define *Age* as the time elapsed from the commercial launch of the brand to the reference current date, August 1st 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 Revenge of the Fallen from the Transformers series released on June 29 2009.
2. **Type of good** – We used the classification of Nelson (1974) and Laband (1986) to divide the brands into *Search*, *Experience* and *Credence* goods. We operationalize this measure, as originally defined, at a subcategory level, which is 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 inter-coder agreement was 72% and the judges resolved all disagreements by consensus.
3. **Complexity** – We measured complexity in our survey using a 5-points scale based on Moore and Benbasat (1991) and Speier and Venkatesh (2002). Our *Complexity* scale includes items on (i) the learning efforts needed to get used to the brand, (ii) the time required to fully understand its advantages, (iii) the difficulty of the product concept, and (iv) the mental effort to use the brand (see the Web Appendix (part 2) for the exact questions). In our brand list, Medicare is perceived as the most complex brand, and Pledge as the least complex.
4. **Knowledge** – We used two variables to measure the level of knowledge about the brand. The first, *Familiarity*, is a single-item 5-points scale included in our survey in which respondents were asked to what extent they are familiar with the brand. The second variable, *Knowledge*, is one of YRBAV's pillars. It is a single-item 5-points scale, in which people are asked to indicate their level of intimate

understanding of the brand. As Table 3 indicates, brands such as Band Aid and Walmart are ranked high on familiarity and knowledge, while more local brands, such as HEB Grocery, of Shaw's Supermarket and ranked low. These two variables, although similar, differ in how detailed or intimate the knowledge is. The correlation between these variables is 0.80. Hence, we use principal component analysis to identify a single factor to incorporate both of these variables. This one factor explains 91% of the variation and both variables load positively (see Appendix 7) for details.

5. **Differentiation** – To measure differentiation we used the YRBAV pillar, *Energized-Differentiation*. *Energized-Differentiation* is a weighted average of items asking 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 the lowest.

6. **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 automobile brand Saab is the least.

7. **Quality** – We measure quality through the last YRBAV pillar, *Esteem*. This variable captures the extent to which people hold a brand in high esteem. It is measured through items asking about the leadership, reliability, and quality of the brand. Tylenol has the highest esteem score and the soap opera Ugly Betty the lowest.

8. **Premium -** Each brand was classified as one of the following three: *Premium*, *Value*, or *Middle*. Classification was done by two independent judges. The inter-coder agreement was 70% and the judges resolved all disagreements by consensus. Classification was done relative to the product type (e.g. *Clinique* was evaluated 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.

9. **Visibility** – We measure *Visibility* as the observability construct of Rogers (1995) using a five-item 5-points scale based on Moore and Benbasat (1991). These survey items ask whether the brand is commonly seen in the environment. The brand with the highest visibility on our list is Microsoft, while

Lamborghini received the lowest visibility score.

10. **Excitement –** We included in our survey a subset of Aaker's (1997) 5-points excitement scale, which we use to measure *Excitement* (including items such as exciting and spirited). The full scale includes items that overlap with other variables in our analysis (e.g., age and differentiation), and as a result leads to inflated standard errors (i.e. multicollinearity). It should be noted 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.

11. **Satisfaction –**We use the American Customer Satisfaction Index, 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). We later discuss how we handle this missing data challenge.

12. **Perceived risk -** Rogers (1995) defines perceived risk as the functional, financial, and emotional uncertainty associated with the product (where emotional uncertainty is the feeling of social embarrassment that might be associated with using the brand). We use the full three item, (5-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.

13. **Involvement -** We use the three-item 5-points scale by Ratchford (1987). 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. Following prior studies, our measure of *Involvement* (collected via 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 the lowest.

Control variables

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

1. **Brand Equity -** We use data from *Interbrand* for measuring brand equity and to capture advertising and media coverage effects. Based on *Interbrand*'s list of top 100 brands during any of the years 2008-2010 we code a binary variable indicating whether the brand is in the list or not. We expect brand equity to increase WOM.

2. **Usage** – We use a measure from YRBAV's survey on the percentage of people who answered that they use the brand frequently or occasionally. Band Aid is scored the highest on usage, and Porche the lowest.

3. **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 (hard to standardize). Accordingly, videogames and movies were classified as products, fashion brands that are sold both in their own stores and in other outlet were classified as mixed, and sports teams as services. The inter-coder agreement was 82% and the judges resolved all disagreements by consensus.

4. **Internet Brand -** Seventeen of the brands on our list, such as eBay, Amazon, Expedia and Google, are Internet based services, and by their nature might be more relevant for online WOM than offline WOM. To control for this factor, we code a binary variable indicating whether the brand is an Internet brand or not.

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 since many of our variables are not available for them. For example, movies and television programs and some sub-brands (e.g., Cherry Coke) do not have data available for *Satisfaction* and 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 dataset contains two dependent variables—online and offline brand mentions (WOM)—and nineteen explanatory variables. Summary statistics for the dependent and explanatory variables are displayed in Table 3. Table 4 presents the correlations for the explanatory variables. These correlations use the full set of brands in our analysis except for correlations with *Satisfaction*, which are calculated using only the 209 brands for which Satisfaction is observed.

Our data is aggregate and based on multiple sources. This means that we do not observe how the brand perceptions of a *specific* individual are translated into her specific WOM. However, these multiple sources also mean that our variables are answered by different sets of individuals. This separation implies our analyses are protected from common methods 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, including 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 non-normal distribution and 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:

$$\mathrm{y}_{\mathrm{ik}}^{m} \sim \mathrm{f}_{\mathrm{NegBin}}(\gamma_{\mathrm{k}}^{m} + \beta^{m}\mathrm{X}_{\mathrm{ik}}, \alpha^{m}) \, ,$$

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 (i) the vector X_{ik} that includes the variables of interest and controls, (ii) the channel-specific linear parameters β^m, and (iii) 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 2/3). As a result, we assume a prior for the missing data and use a missing-at-random (MAR) assumption in order to impute values for the missing observations. Specifically, 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:

$$X_{ik}^{I} \sim f_N(\bar{X}^C, V(X^C)),$$

where the function f_N is the normal density, X_{ik}^{I} is the incomplete observations of *Satisfaction*; X_{ik}^{C} are the complete observations of *Satisfaction*, $\bar{X}^C$ is the mean of the complete data, and $V(X^C)$ is the variance of the complete data. Note that while the prior is only based on the complete *Satisfaction* data, the posterior distribution is influenced by the full model likelihood. As a result, and since the observations in *I* are incomplete only with respect to one variable, the posterior distribution of the imputed data, X_{ik}^{I}, also depends on the relationship to all the other variables. We note that this Bayesian approach is consistent with the likelihood-based approach suggested by Schafer and Graham (2002) and naturally accommodates multiple imputations through the posterior simulation. The Web Appendix (part 6.3) presents robustness checks against alternative imputation procedures.

To complete the model, we describe the other priors, starting with the category-level effect. Our brand observations come from a large 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 rest is random from our perspective. Thus, we use a multi-level model, allowing the category level effects to be a function of involvement, an overall average, and a random effect. Specifically, the prior distribution for the *k*th category-level effect on channel *m* WOM, γ_{k}^{m}, is

$$\gamma_{\mathrm{k}}^{m} \sim \mathrm{f}_{\mathrm{N}}(\delta^{m}\mathrm{Z}_{\mathrm{k}}, \sigma_{m}^{2}),$$

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: $\beta^{m} \sim f_{N}(\bar{\beta}^{m}, A^{-1})$; $\alpha^{m} \sim f_{GAM}(a_{0}, b_{0})$; $\delta^{m} \mid \sigma_{m}^{2} \sim f_{N}(\bar{\delta}^{m}, \sigma_{m}^{2} A_{\delta}^{-1})$; $\sigma_{m}^{-2} \sim f_{\chi^{2}}(\eta_{0}, v_{0})$

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 $\pi\left(\theta^{m}\right)$ 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

$$\left[\prod_{i=1}^{n} \mathrm{f}_{\mathrm{NegBin}}(\gamma_{\mathrm{k}}^{m} + \beta^{m}\mathrm{X}_{\mathrm{ik}}, \alpha^{m}) f_{N}(\bar{X}_{ik}^{C}, V(X_{ik}^{C}))\right] \prod_{k=1}^{K} \mathrm{f}_{\mathrm{N}}(\delta^{m}\mathrm{Z}_{\mathrm{k}}, \sigma_{m}^{2}) \pi\left(\theta^{m}\right)$$

We estimate the model using Markov Chain Monte Carlo posterior simulation. Details related to the estimation are presented in the Web Appendix (part 3).

Results from the Full Model

The full model results are presented in Table 5. We organize our discussion below by the drivers.

The Social Driver

We begin our discussion with our focal variable related to this driver, the level of product differentiation. Recall that this characteristic was identified by our theoretical framework (in relation to the desire to express uniqueness), and that it was not studied yet in the context of WOM. As expected by the theoretical framework differentiation (measured by YRBAV's *Energized-Differentiation*) has a positive and significant effect on WOM both online and offline. This means that people tend to talk more on differentiated brands than on other brands. Interestingly, as suggested in the theoretical framework section, the effect is much stronger in the online setting than in offline conversations (1.78 versus 0.62). Recall that this might be due to two fundamental differences between online and offline: first, in offline interactions an individual has many ways to communicate uniqueness (e.g., 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 individuals who are less familiar with one's personality, leading to a stronger desire to express one's personality and especially one's uniqueness. Differentiation is not the only characteristic in which interesting differences exist between online and offline. In order to provide a comprehensive picture of these differences we devote a special discussion to them at the end of this section instead of a separate discussion for each one.

The second motive under the social driver is the desire to enhance one's self by associating with high quality products in order to demonstrate expertise (measured by *Esteem*) and by signaling higher status (via *Premium* products). The results for *Esteem* are consistent with these expectations for both online and offline, indicating that brands with higher perceived quality are mentioned more often. When it comes to *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 online and offline channels. For *Relevance* we find a significant, positive effect offline, but a negative insignificant effect online. As mentioned above, such differences are discussed in a special subsection focusing on online-offline differences.

The Emotional Driver

The emotional driver includes two characteristics, *Excitement* and *Satisfaction*. We first consider our focal variables for this driver, *Excitement*, which was not yet studied 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 the 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. Based on 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 of satisfaction. To capture this potential shape, we included in the model linear and quadratic terms for *Satisfaction*. However, in both the online and offline channels we find a monotonic concave effect. Over the observed values of satisfaction (between 55 and 89) we find that as satisfaction increases, WOM decreases. This result means that the higher WOM at low satisfaction levels is supported by the data, but the higher WOM for high satisfaction levels is not. It is possible that earlier findings about the high WOM at high satisfaction levels were due to the exclusion of variables such as *Esteem* and *Excitement* that are related to *Satisfaction* and are included in our model. In other words, our analysis studies the role of satisfaction over and beyond the effect of these variables.

The Functional Driver

The functional driver relates to the need to obtain information, and the tendency to provide information. We begin by discussing our focal variable for this driver, *Complexity*, which was not yet studied in the context of WOM. The effect of *Complexity* has the expected positive sign and the estimates are statistically significant for offline, but for online the effect is negative and marginally significant (p-value<0.1). In other words, people talk more in the offline world about brands that are more complex, but online they talk more about brands that are less complex. Interestingly, we find a similar pattern (significant and negative offline, insignificant online) for *Age*, indicating that newer brands are more likely to be discussed than older brands offline. Turning finally to *Type of good*, we find that for online channels, Search goods are mentioned statistically less often than Experience goods, but for offline, 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 types of 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 the Web Appendix (part 4), 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 discussed above, two characteristics (*Perceived risk* and *Involvement*) do not fit nicely into only one driver and thus are considered as "hybrid" (i.e., they contain elements of multiple drivers). As 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 since it is measured at the category level, and with only 16 categories, the limited variation did not allow us to effectively estimate the effect. We do not find a significant effect in any of the models.

Controls and Dispersion

All of 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 vs. Offline

While some variables have a very similar coefficient in the online and offline settings (e.g. the coefficients of the *Knowledge factor* are 0.49 and 0.46, respectively) others differ meaningfully either in their coefficients and/or in their significance between the two settings. To get a clear picture of these differences we discuss them together here. Note that for each variable we can directly compare the coefficients from the online and offline regressions, since the dependent variables are logged and the independent ones are the same. As a result, in both regressions the coefficients represent the percent 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 have already 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*, where the coefficient is significant for both online and offline, but it 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 above, that individuals seek to enhance the self more online than offline perhaps due to the lack of non-verbal cues (e.g., what brands one wears) to help signal one's status and identity, and the broadcasting nature of the online medium. In contrast, while *Visibility* is similarly strong across online and offline, *Relevance* is significant and positive offline, while negative and not significant online. This difference could be due to the diversity of tastes of the broader audience online that implies that even brands with lower relevance are still relevant for many and thus can serve as conversation material – e.g. a fan of an indie band may find few fans offline but many online and thus its low relevance does not suppress online WOM.

The coefficients of the emotional driver are essentially the same across channels, so we turn next to those of the functional driver. Here, the most interesting variables are *Age* and *Complexity*. Less complex brands have more WOM online, while more complex brands get more WOM offline. One possible explanation for this difference could hinge on the advantages of offline conversations in clarifying complex issues because such conversations are truly interactive and allow questions-and-responses and clarifications. In contrast, online conversations are more likely asynchronous (Morris and Ogan 1996), taking 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. The similar result for *Age* can be explained by this same argument.

That said, as we illustrate later (see Robustness checks subsection), our results are quite robust, but the estimate of *Complexity* is perhaps least so. Furthermore, one might argue that the lack of effect online (and even marginally significant opposite effect) is due to not observing individuals passively reading (i.e., receiving, but not posting) information (see Yang et al. 2012 on the differences between WOM generation and consumption). By considering both online and offline data together, we can empirically see the potential effects of this possible shortcoming of the typical online data sources.

Results on Relative Importance of the Three Drivers of WOM

To compare the importance of the variables under the three drivers at once, we ask what happens to the fit of the model when each of these drivers is excluded 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 larger 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 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 part 5). 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 then 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 lastly social, with the importance of the emotional driver being significantly greater than the other two drivers. In other words, while the emotional driver is the most important in offline conversations, the social one is the major force in online brand mentions. These results portray an interesting and insightful picture of WOM. One way of interpreting them is to argue that offline conversations, which are mostly in one-on-one settings, are more personal and intimate by nature and thus allow people to share emotions such as excitement and satisfaction. In contrast, online WOM, which usually involves "broadcasting" to many people (e.g. Twitter) and where non-verbal signals are not available, is more appropriate for social signaling (e.g. of uniqueness).

An alternative explanation of these results is that they are driven primarily by the difference in measurement between online and offline. 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 emotional characteristics. While we cannot rule this alternative out, some aspects of the data minimize this possibility. First, the self-reports are collected only for one day per respondent, who are requested to keep the diary with them at all times, minimizing the lag between occurrence and reporting. Second, the data provider, the Keller-Fay Group, ran additional checks where respondents used smart phones and recording devices to examine whether pure observational behavior differed from the self-reports. They found that the pattern of observed word-of-mouth was similar to the self-reported one.

Results on the connection between brand characteristics and WOM content

While our study relates brand characteristics with WOM mentions, it is possible that these characteristics relate also to WOM content. For example, it is possible that exciting brands, such as *Arizona Beverage*, do not just get more WOM, but the content of the WOM expresses more excitement about the brand. While extending our theoretical and empirical framework to address such an issue is beyond the scope of this study, it is interesting to see whether such a content-characteristic connection is likely via a small-scale test.

For such a test we focused on (i) three characteristics (*Excitement*, *Esteem*, and *Differentiation*), (ii) 10 major product categories, and (iii) 41 brands that were selected to provide a range of scores above and below average for these three characteristics. Using a commercial text-mining tool (NetBase'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 automobiles – "great experience", "popular model", and "head turning" and 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 in the past 365 days as well as the total brand mentions. Thus, for each brand and characteristic we had a "content score", which is the number of times this characteristic was mentioned with respect to this brand divided by the total mentions.

Using this 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 allow the relevant characteristic to affect the content score (e.g., *Excitement* affects the *Excitement Content Score*). Hence, the model for *Excitement* is

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

The results are presented in Table 7. The coefficients for all three characteristics are positive and two out of three are significant, suggesting that brand characteristics increase the proportion of brand mentions that involve content related to the specific brand characteristic. While these results are obviously 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 above analyses, we have also conducted a range of robustness tests in order to ensure that our results are not influenced severely by selection biases, multicollinearity, outliers, or the missing data model. The complete set of analyses is discussed in Web Appendix (part 6). We note a few highlights here.

Selection bias: Our analysis is based on the 600 plus 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 dataset, the order of the three drivers remain the same – i.e., the social driver is most important for online WOM and the emotional is most important for offline. Of course, some coefficients change in effect and significance as we decrease the sample size, but, overall, it appears that the significant effects are relatively robust to sample selection biases. See Web Appendix (part 6.1) for details including the richness of results across the different sets of brands. For instance, it appears that *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 section (part 6.2) for details.

Missing data: First, we note that our approach to modeling the missing data is consistent with what is recommended 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, in order to get yet another view on 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, but 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 our approach. See Web Appendix (part 6.3) for details.

Outliers: We find relatively minor outlying cases (with absolute standardized residuals less than 4) and dropping these cases had no impact on the statistical significance or direction of effects. See Web Appendix (part 6.4) for details.

Discussion

Although brands and WOM are two fundamental marketing concepts, their relationship has largely been ignored. 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 according to which the brand characteristics affect WOM through three drivers –social, emotional, and functional.

The results portray a nuanced, intricate picture for the brand-WOM relationship in two aspects: First, all three drivers -- social, emotional, and functional -- play a role. In other words, WOM is not related to only one characteristic (e.g. perceived risk or visibility), or driver. All the different facets of the brand are involved. Second, the role of brand characteristics differs across the WOM channels. For example, new brands are talked about more offline, but we find no support for this relationship online. In contrast, premium brands have significantly more online brand mentions while we find no support for such a relationship offline. Furthermore, the channels differ in what fundamental drivers are most important to WOM - while 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 a decade ago WOM was largely considered a side effect of marketing activity. Not anymore. Today, marketers are trying to develop a systematic approach to manage it.[6] Our work might be able to assist in

[6] In this context, for example, practitioners debate whether WOM and advertising are complementary or substitute to each other (see Armelini and Villanueva 2010 for review and the discussion in the first annual meeting of WOMMA, the main professional association for WOM marketing).

this task. As demonstrated in the next four points, it can provide practitioners with tools in planning, measuring and managing not only their WOM initiatives, but also their marketing mix as a whole as well as their branding practices.

1. **Connect brand characteristics and WOM** – Marketers are very interested in creating "Talkable Brands" (e.g. that was the motto of WOMMA's – the professional association for WOM marketing – annual summit in 2012). Our findings can assist them in identifying the brand characteristics that can do this job. A brand manager that wants to have 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. Since visibility enhances WOM and our model can project the magnitude of the effect, a brand manager may be able to weigh in the total costs and benefits of the design choice. The 1999's "Intel Inside" campaign did something very similar –it increased the visibility of the microprocessor and contributed to the firm's WOM (Intel is on our list of 700 brands).

   In order to assist managers in such an evaluation task, we created a model-based Descriptive Decision Support System (DDSS) in 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 et al. 2007). Specifically, by comparing the expected level of WOM to the actual level, one can see if 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 Dove, TGI Fridays, and Coca Cola do exceptionally well offline (i.e., a large positive gap between actual and expected). On the other hand, America Online, Charter communications and Mug Root Beer do poorly both offline and online compared to what we would expect based on their brand characteristics. Interestingly, brands such as Facebook, Staples and Cheerios, meet or exceed the expectations online but underperform offline. Managerially, this could call for more focus on exploiting 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 per-se 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 some categories, such as financial products. Indeed, being aware of your WOM potential should shape how brands set marketing communications objectives and strategies.

2. **Online and offline WOM are quite different** – We already know that while some brands (e.g. Google Audi, and Ebay) have a strong and active online WOM presence, others (e.g. Coca Cola, WalMart, and 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, it means that copying methods that led to success in one medium of communications (say online) 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 the word on it. Second, it means that following the trend of relying on measures of online WOM (e.g. NMIncite Buzzmetrics, Brandwatch, Netbase, and Radian6) to assess your success in stimulating a conversation on your brand might not be a good idea. Our findings imply that such measures might not be relevant for some managers. Interestingly, we have recently heard expression of frustration from a manager of several well-known household brands because she believes that most of the WOM for her brands comes from offline channels, yet her performance is being 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, since much of it has been conducted on online channels – e.g. the carryover of WOM referrals in social networking sites (Trusov et al. 2009), the impact of WOM on TV viewing (Godes and Mayzlin 2004), or the tone and style of WOM in blogs (Kozinetz et al. 2010). These findings are valid for the channels they were measured in, but generalizing them to offline channels should be done carefully.

3. **A novel benefit of product differentiation -** Product differentiation is a key concept in marketing strategy. Brand managers are advised to determine both points of parity and points of differentiation. To justify the costs of creating differentiation, scholars attempt to explore their benefits and discuss conditions under which differentiation should be pursued (Schmalensee 1982; Dube 2004; Bronnenberg 2008). Our work contributes to the discussion by identifying a novel benefit of product differentiation over and 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. This might 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.
4. **Justify investment in brands -** The large investment in branding has been driving 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 (Stahl et al. 2012; Leone et al. 2006). It is argued that strong brand association leads to enhanced identification and loyalty which are then translated 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 word of mouth. All four pillars used by Young and Rubicam 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 helps in the efforts to reach a more comprehensive understanding of the return on branding.

Limitations and Future Research

Of course, our study has its limitations. Since 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, *once 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 it contains only the most talked about brands. As a result, our findings may not be applicable to brands with relatively little WOM. While we have provided some evidence on the robustness of our findings to the selected sample, our data cannot completely rule out this possibility.

Another point to keep in mind is that we relied on measures of aggregate brand mentions rather than ones disaggregated by source. While this aggregation allows us to speak on WOM across many different brands, categories and channels, one might get a clearer picture as to mechanisms underlying specific channel effects through more disaggregate data. Future research could use finer grained data to study these and other, more nuanced, questions.

Along these lines, this work lays the ground for future research in several directions:

1. *Channel effects* - In this paper we focused on the relationship between brand characteristic 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 future research. Instead of the gross division to offline and online, more channels can be explored. Various online channels – i.e., emails, Twitter, Blogs and User groups – are different in nature and can show different patterns of WOM. Gaining a better understanding of these dynamics of WOM across channels can help shape strategies for generating WOM, responding to WOM issues, and for identifying leading and lagging indicators of WOM.

2. *Valence and content*- In this study, we counted the overall mentions of WOM, regardless of the 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 interesting because of its possible impact on adoption and purchase behaviors. Previous studies explored the implications and contexts of negative WOM (e.g. Moldovan et al. 2011); however, the antecedents of negative WOM received little research attention. As

for the content, we presented some preliminary evidence indicating that brand characteristics are also relevant for WOM content, but further research can shed some additional light on the characteristics-content relationships.

3. *Individual level insights* – This study examines WOM behaviors at the brand level, using aggregate measures of WOM. As a result, we cannot make claims on the WOM behaviors of individuals. For example, do the online-offline differences we demonstrated 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 that track the WOM process at the individual level. To our knowledge, no such dataset exists, but building such a dataset could greatly enhance the ability to understand WOM behaviors at the individual level.

4. *Moderators of the brand characteristics-WOM relationship* -- While 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 research could explore such moderating roles.

The goal of our paper is to better understand the intricate relationships between brands and WOM. We believe that such an understanding can benefit both research on WOM and research on brands. The research on WOM will benefit from understanding the antecedents of WOM, its patterns, and channel interactions. Branding research will benefit since WOM is an indicator for market response. This paper takes a first step in linking these two literatures and providing insight into fruitful areas of future research.

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Tables and Figures

Figure 1: Theoretical framework – matching WOM drivers, brand characteristics and WOM

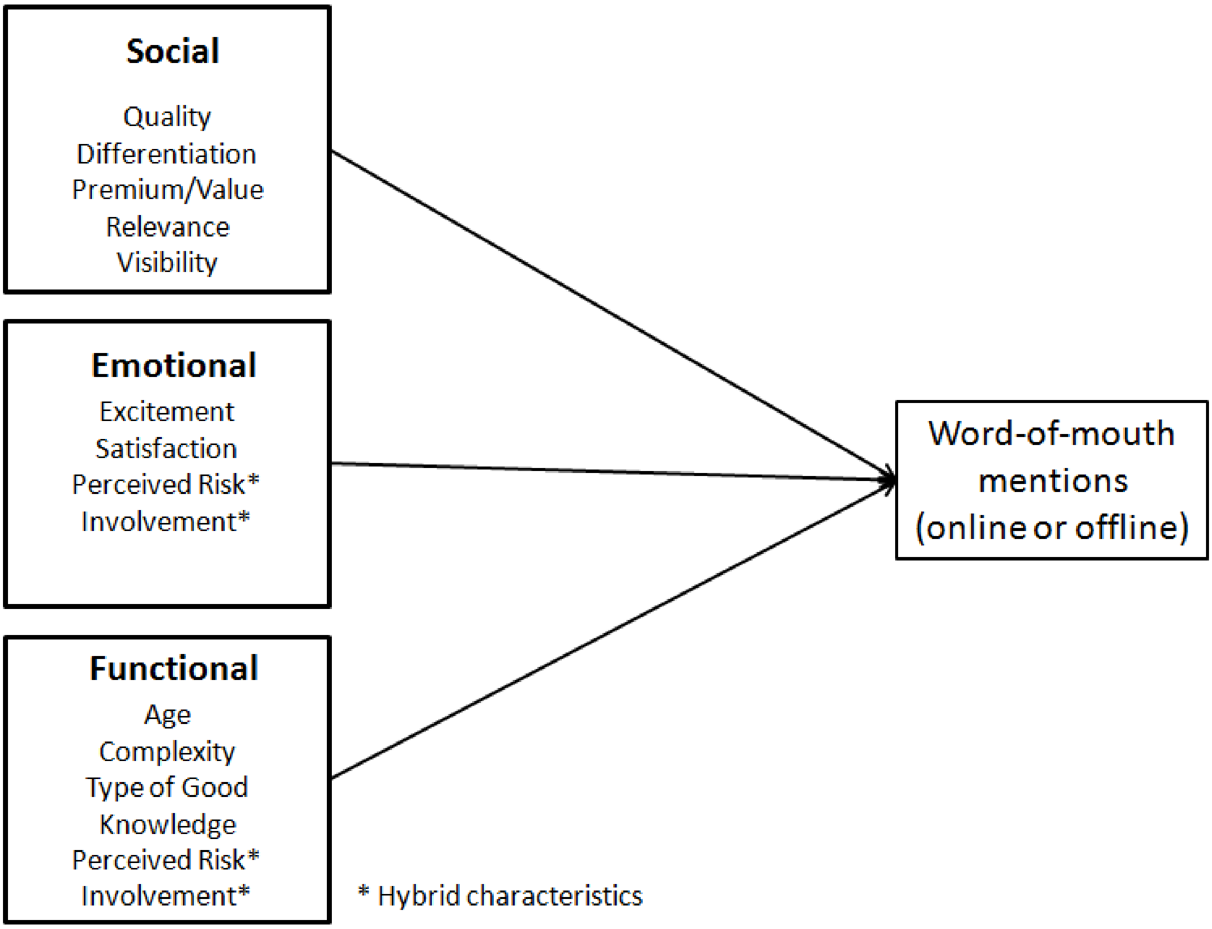


Figure 2: The list of data sources

Explanatory variables

Decipher Inc
Complexity, Visibility, Involvement, Excitement, Familiarity, Perceived Risk

Brand Asset Valuator by Y&R
Differentiation, Relevance, Esteem, Knowledge, Usage, Satisfaction

Interbrand
Brand equity – is part of the top 100?

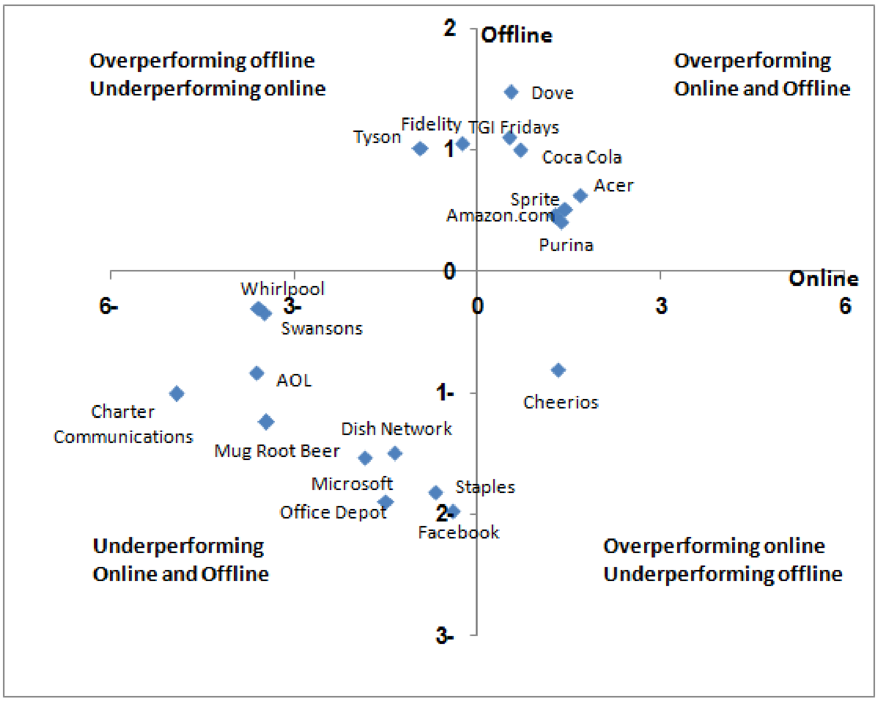
Secondary data collection
Age, Type of good, Product/Service, Premium/Value, Internet brand

Dependent variables

The Keller Fay group
Offline word of mouth

NMIncite Buzzmetrics
Online word of mouth

Figure 3: Actual vs. Predicted Performance of Top 2% of overperforming and underperforming brands



The WOM performance of brands is measured 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, but not the brand level random effects.

Table 1: Top 10 most mentioned brands offline and online

Order	Offline	Online
1	Coca Cola	Google
2	Verizon	FaceBook
3	Pepsi	iPhone
4	WalMart	YouTube
5	Ford	Ebay
6	AT&T	Xbox 360
7	McDonalds	Ford
8	Dell Computers	Yahoo
9	Sony	Disney
10	Chevrolet	Audi

#

Table 2: Distribution of total mentions and mentions per brand, offline and online

		% Total mentions		Average mentions per brand	
Category	**Number of brands**	**Online**	**Offline**	**Online**	**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

Note that: 1. The sample contains only the most talked about brands. 2. The online numbers contain mentions from all the available sources, while the offline numbers only contain mentions from a weekly representative sample of 700 people. Importantly, as a result, the numbers for offline cannot be directly compared to those for online.

Table 3: Summary statistics

	Mean	Std. Dev.	Min	25%	50%	75%	Max	Max value brand	Min value brand	Obs. Used
Dependent										
Online Brand Mentions (/1,000,000)	0.43	1.12	0	0.03	0.08	0.33	14.58	Vault Energy Drink	Google	613
Offline Brand Mentions (/1,000)	0.86	1.46	0.12	0.24	0.41	0.84	15.04	Coca Cola	America's got Talent	613
Social										
Differentiation	0.49	0.16	0.17	0.39	0.46	0.57	1.12	Food Network	Days Inn	613
Esteem	0.61	0.3	0.09	0.38	0.55	0.77	1.67	Tylenol	Ugly Betty	613
Middle (VP)	0.51	0.5	0	0	1	1	1			613
Premium (VP)	0.26	0.44	0	0	0	1	1			613
Relevance	2.74	0.72	1.39	2.13	2.65	3.24	4.75	Kraft	Saab	613
Visibility	3.01	0.37	1.79	2.78	3.02	3.27	3.99	Microsoft	Lamborghini	613
Emotional										
Excitement*	3.28	0.4	2.05	3	3.27	3.54	4.51	iPhone	Medicare	613
Satisfaction (/50)	1.59	0.13	1.1	1.5	1.63	1.69	1.79	Heinz	Charter Communications	201
Functional										
Age (/50)	1.11	0.76	0.04	0.5	0.96	1.61	4.09	Colgate	Transformers: Rev. of the Fallen	613
Search	0.21	0.41	0	0	0	0	1			613
Credence	0.07	0.25	0	0	0	0	1			613
Complexity	1.82	0.38	1.01	1.53	1.81	2.06	3.03	Medicare	Pledge	613
Familiarity	3.36	0.59	1.48	2.92	3.42	3.79	4.62	Band Aid	HEB Grocery	613
Knowledge	3.54	0.88	0.73	3.02	3.71	4.18	5.16	Walmart	Shaw's Supermarket	613
Hybrid										
Perceived risk	1.79	0.31	1.02	1.54	1.81	2.01	2.62	Medicare	Dr. Pepper	613
Involvement	3.72	0.36	3.09	3.52	3.62	3.97	4.38	Financial Services	Beverages	613
Controls										
Interbrand_top_100	0.12	0.33	0	0	0	0	1			613
Usage (/50)	0.67	0.45	0.01	0.29	0.58	1	1.79	Band Aid	Porche	613
Mixed (PS)	0.03	0.17	0	0	0	0	1			613
Service (PS)	0.43	0.5	0	0	0	1	1			613
Internet Brand	0.03	0.16	0	0	0	0	1			613

* This is the average of the three excitement items from Aaker questionnaire as described in the data section.

Table 4: Correlations

	Diff	Estm	Midl (VP)	Prem (VP)	Rel	Visi	Exct	Satis	Age/50	Srch	Cred	Cmpl	Know Fac	Per Risk	IB 100	Usage (/50)	Mix (PS)	Svc (PS	Inter -net
Diff	1	0.1	-0.15	0.3	-0.01	0.09	0.57	0.19	-0.31	0.1	-0.15	0.12	0	0.07	0.22	-0.03	0.17	-0.09	0.11
Estm	0.1	1	0.05	-0.05	0.8	0.51	-0.15	0.23	0.35	0.04	-0.03	-0.42	0.68	-0.49	0.22	0.58	-0.03	-0.25	-0.01
Midl (VP)	-0.15	0.05	1	-0.58	0.04	0.09	-0.15	-0.16	0.07	0.02	0.17	-0.02	0.02	-0.06	0.01	0	0.03	-0.12	0.08
Prem (VP)	0.3	-0.05	-0.58	1	-0.17	-0.1	0.26	0.17	-0.03	0	-0.09	0.17	-0.11	0.13	0.08	-0.16	0.01	0.04	-0.05
Rel	-0.01	0.8	0.04	-0.17	1	0.54	-0.2	0.25	0.25	0.03	-0.11	-0.62	0.7	-0.67	0.08	0.85	-0.07	-0.18	0
Visi	0.09	0.51	0.09	-0.1	0.54	1	0.07	0.13	0.11	0.07	-0.15	-0.5	0.51	-0.5	0.17	0.45	0.01	-0.2	-0.06
Exct	0.57	-0.15	-0.15	0.26	-0.2	0.07	1	0.24	-0.29	0.1	-0.2	0.08	-0.1	0.02	0.07	-0.13	0.09	-0.07	-0.01
Satis	0.19	0.23	-0.16	0.17	0.25	0.13	0.24	1	0.13	0.07	-0.1	-0.54	0.23	-0.6	0.06	0.23	0.03	-0.61	-0.18
Age/50	-0.31	0.35	0.07	-0.03	0.25	0.11	-0.29	0.13	1	-0.01	0.09	-0.16	0.24	-0.18	0.11	0.14	-0.01	-0.12	-0.16
Srch	0.1	0.04	0.02	0	0.03	0.07	0.1	0.07	-0.01	1	-0.13	0.02	-0.03	0.04	0.08	0.01	0.13	-0.15	-0.06
Cred	-0.15	-0.03	0.17	-0.09	-0.11	-0.15	-0.2	-0.1	0.09	-0.13	1	0.31	-0.17	0.17	-0.02	-0.18	-0.05	0.12	0.07
Cmpl	0.12	-0.42	-0.02	0.17	-0.62	-0.5	0.08	-0.54	-0.16	0.02	0.31	1	-0.56	0.81	0.04	-0.65	0.01	0.35	0.14
Know Fac	0	0.68	0.02	-0.11	0.7	0.51	-0.1	0.23	0.24	-0.03	-0.17	-0.56	1	-0.52	0.13	0.72	-0.04	-0.17	-0.01
Per Risk	0.07	-0.49	-0.06	0.13	-0.67	-0.5	0.02	-0.6	-0.18	0.04	0.17	0.81	-0.52	1	0	-0.64	0.07	0.36	0.06
IB 100	0.22	0.22	0.01	0.08	0.08	0.17	0.07	0.06	0.11	0.08	-0.02	0.04	0.13	0	1	-0.01	0.04	-0.16	0.09
Use (/50)	-0.03	0.58	0	-0.16	0.85	0.45	-0.13	0.23	0.14	0.01	-0.18	-0.65	0.72	-0.64	-0.01	1	-0.07	-0.08	0.01
Mix (PS)	0.17	-0.03	0.03	0.01	-0.07	0.01	0.09	0.03	-0.01	0.13	-0.05	0.01	-0.04	0.07	0.04	-0.07	1	-0.16	-0.03
Svc (PS)	-0.09	-0.25	-0.12	0.04	-0.18	-0.2	-0.07	-0.61	-0.12	-0.15	0.12	0.35	-0.17	0.36	-0.16	-0.08	-0.16	1	0.18
Internet	0.11	-0.01	0.08	-0.05	0	-0.06	-0.01	-0.18	-0.16	-0.06	0.07	0.14	-0.01	0.06	0.09	0.01	-0.03	0.18	1

Table 5: Estimation results

	Online		Offline	
Variable	**Posterior Mean**	**(95% CI)**	**Posterior Mean**	**(95% CI)**
Social				
Differentiation	1.78**	(0.90, 2.65)	0.62**	(0.16, 1.12)
Esteem	1.22**	(0.66, 1.79)	0.52**	(0.22, 0.81)
Middle (VP)	0.50**	(0.31, 0.69)	0.01	(-0.09, 0.10)
Premium (VP)	0.47**	(0.19, 0.75)	-0.07	(-0.21, 0.06)
Relevance	-0.26	(-0.62, 0.06)	0.29**	(0.10, 0.47)
Visibility	0.92**	(0.65, 1.17)	0.72**	(0.53, 0.91)
Emotional				
Excitement	0.71**	(0.39, 0.99)	0.44**	(0.27, 0.60)
Satisfaction	4.60*	(-0.54, 9.75)	5.59**	(3.21, 8.17)
Satisfaction^2	-3.56**	(-5.25, -1.94)	-3.10**	(-3.93, -2.30)
Functional	#	#	#	#
Age	0.13	(-0.07, 0.37)	-0.17**	(-0.29, -0.05)
Search	-0.30**	(-0.56, -0.06)	0.04	(-0.11, 0.27)
Credence	-0.01	(-0.37, 0.37)	-0.60**	(-0.81, -0.39)
Complexity	-0.49*	(-0.98, 0.05)	0.43**	(0.09, 0.76)
Knowledge factor	0.49**	(0.33, 0.65)	0.46**	(0.36, 0.56)
Hybrid				
Perceived risk	0.91**	(0.30, 1.44)	0.03	(-0.26, 0.32)
Involvement	-0.58	(-2.01, 0.85)	0.13	(-1.01, 1.25)
Controls				
Category Avg	8.36**	(1.67, 15.37)	-0.73	(-5.34, 4.01)
Interbrand_top_100	0.95**	(0.74, 1.17)	0.26**	(0.14, 0.39)
Usage	-1.07**	(-2.22, -0.13)	-0.84**	(-1.36, -0.28)
Mixed (PS)	-0.36	(-0.99, 0.34)	0.27	(-0.15, 0.62)
Service (PS)	0.54**	(0.23, 0.79)	0.62**	(0.49, 0.77)
Internet Brand	0.31	(-0.08, 0.70)	-0.30**	(-0.49, -0.10)
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).

Table 6: Relative Importance of the Functional, Social and Emotional drivers

	Online	Offline
	LML*	LML
Models with the Hybrid characteristics		
Social	-8393.6	-5745.4
Emotional	-8455.9	-5312.0
Functional	-8439.4	-5374.4
Social & Emotional	-8376.5	-5640.2
Functional & Emotional	-8424.1	-5536.9
Functional & Social	-8392.4	-5899.7
Models without the Hybrid characteristics		
Social	-8381.8	-5707.7
Emotional	-8453.5	-5316.1
Functional	-8454.2	-5408.8
Social & Emotional	-8387.3	-5573.1
Functional & Emotional	-8412.6	-5363.8
Functional & Social	-8358.4	-5867.0

* LML indicates log marginal likelihood with higher (less negative) values indicating better fit to the data.

This table indicates that for submodels containing only one driver, online the social driver fits best (LML=-8394) and functional second best (LML=-8439), while offline, the emotional driver fits best (LML=-5312) and functional second best (LML=-5374). Similarly the same relationship holds for submodels containing one driver and including the hybrid motives. For submodels containing two drivers, the best models online contain social and the best models offline contain emotional. This pattern is true for both models with and without the hybrid characteristics.

Table 7: The relationships between brand characteristics and content score

Content score	Brand characteristic		
	Excitement	Esteem	Differentiation
Log (excitement)	0.29** (0.12)		
Log (esteem)		0.01 (0.13)	
Log (differentiation)			0.43** (0.21)

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