Summer 7-12-2011

How Does Buzz Build Brands? Investigating the Link between Word of Mouth and Brand Performance

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HOW DOES BUZZ BUILD BRANDS?
INVESTIGATING THE LINK BETWEEN WORD OF MOUTH AND BRAND PERFORMANCE

By

Andrew M. Baker

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY

ROBINSON COLLEGE OF BUSINESS

2011

ACCEPTANCE

This dissertation was prepared under the direction of Andrew M. Baker's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctoral of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

How Does Buzz Build Brands? Investigating the Link Between Word of Mouth and Brand Performance

BY

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July 2011

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Marketers have long been interested how word of mouth (WOM) contributes to marketing performance. However, there is a dearth of systematic investigation into how different characteristics of WOM episodes affect consumer response toward brands partly because of the difficulties associated with collecting detailed WOM information. To aid in resolving some of the ambiguity in the literature about the impact of different forms of WOM on brand performance, this dissertation investigates how WOM influences three consumer responses to WOM: purchase, WOM retransmission, and additional information search. The author investigates these questions by analyzing a database comprising more than three years of detailed WOM data from a unique, nationally representative panel merged with other secondary sources that provide various measures of brand strength (the American Consumer Satisfaction Index and Harris Interactive's Equitrend). The analysis includes 188,510 WOM conversations across 654 brands. Using a series of hierarchical regression models, the results from this study reveal numerous insights into the contextual factors that moderate the impact of a WOM episode. For example, negative WOM about a brand has a larger absolute effect on consumer purchase intentions than positive WOM, but positive WOM has a larger positive effect on WOM retransmission than the positive effect of negative WOM. Offline WOM tends to exacerbate the effect of positive and negative brand sentiment on purchase intentions. WOM between stronger social ties tends to have greater impact on brand-related responses than WOM between weak ties, except in the case of motivating additional information search. The results also indicate that strong brands (those with higher levels of brand equity) tend to reap greater benefits from WOM. For example, negative, mixed, or neutral WOM has greater influence on purchase, and WOM from weak social ties about strong brands motivates

higher levels of information search than when WOM from weak ties is about weaker brands. Because the most (or least) desirable forms of WOM vary depending on characteristics of the brand and the marketer's consumer response objective, the results of this dissertation provide insight for brand managers who are interested in monitoring and influencing the nature of WOM about brands.

SUMMARY

Word of mouth (WOM) is one of the most persuasive, influential, and widely studied sources of consumer information. Much is known about drivers and moderators of WOM activity (de Matos and Rossi 2008) and how WOM affects immediate consumer attitudes. However, despite marketers adopting tactics to leverage WOM (Li and Bernoff 2008), difficulties associated with measuring natural, organic WOM (Rust et al. 2000) have hampered insights into WOM's effect on long-term marketing performance. To contribute to this important area, this dissertation examines how the performance of brands is affected by WOM by linking the reception of brand-related WOM to immediate brand-related consumer responses. Linking WOM to brand performance is particularly important because brands are one of the most important intangible assets under marketing managers' care (Keller and Lehmann 2006). Moreover, WOM is a powerful mechanism that affects consumers' brand awareness and brand associations, which are considered the two lynchpins of brand equity (Keller 1993).

Using a unique longitudinal database that tracks WOM of more than 1,000 brands from a nationally representative panel, this dissertation investigates how WOM is linked with immediate consumer response (purchase, retransmitting the WOM, and seeking out additional brand information) and how overall WOM for a brand is linked to brand equity. By using both consumer-level and firm aggregate indicators of brand performance, this dissertation provides insights into (1) the immediate effect of WOM on consumers and (2) how aggregate WOM volumes are linked with estimates of brand value (brand equity). Thus, this dissertation provides insights for frontline managers responsible for monitoring and managing WOM in specific

campaigns as well as marketing executives responsible for building the financial value of intangible assets.

This study is novel for additional reasons. First, a review of extant literature suggests this is the first study to simultaneously examine online and offline WOM (Godes et al. 2005), and this study demonstrates differential WOM impact across the two channels. Second, this study first demonstrates WOM impact at the micro level (e.g., immediate consumer response to WOM) and then demonstrates how the aggregate of these micro-level phenomena links to financial aggregates of brand performance. Third, this study suggests a novel mechanism for how brand-level customer satisfaction and brand equity (both intangible market-based assets) drive future marketplace success for brands. This study demonstrates that the *potency* of WOM on consumer response is favorable for stronger brands; this insight partially complements but also challenges conventional wisdom that stronger brands reap greater WOM benefits primarily by virtue of more positive WOM. Fourth, this study uses actual WOM rather than WOM proxies, thus providing a platform to test the generalizability of WOM insights derived from studies of proxies of WOM (e.g., Luo 2009; Trusov et al. 2009; Villanueva et al. 2008).

INTRODUCTION

Marketers' interest in monitoring WOM activity and influencing WOM patterns (e.g., viral marketing, referral rewards programs, social media marketing) is apparent (Godes and Mayzlin 2009; Luo 2009; Villanueva et al. 2008). Of particular interest is how to link WOM to marketing performance, though difficulties associated with measuring and estimating WOM effects has hampered advances in this field (Rust et al. 2004b). However, as the credibility of

advertising wanes (Darke and Ritchie 2007) and calls for marketing's financial accountability persist (MSI 2010),the need amplifies to understand how the powerful—but less controllable—currents of WOM drive marketing performance.

This dissertation investigates the relationship between WOM activity and brand performance at both the consumer level (individual response to a WOM episode about a brand) and the aggregate level (brand equity). First, an extensive literature review of WOM studies in marketing is performed in which particular emphasis is placed on studies purporting to link WOM to marketer-relevant outcomes (e.g., purchase intentions, sales, brand equity). Then two empirical studies investigate how WOM relates to marketing outcomes. The research questions for the investigations are analyzed using a unique database that integrates publicly available databases of longitudinal, brand-level characteristics with a proprietary database that captures consumer WOM about brands. This nationally representative, longitudinal WOM database captures a multitude of rich WOM dimensions. Investigation 1 examines how characteristics of the WOM communication, social dyad, channel, and brand affect immediate response to WOM (purchase, retransmission of the message, and seeking out additional brand information). Investigation 2 tests whether brands with different levels of overall satisfaction and brand equity tend to experience different consumer-level outcomes from WOM episodes. Together, these investigations reveal insights into the WOM impact not heretofore empirically demonstrated in extant marketing literature and provide practical marketing insights for brand managers.

CHAPTER 1: LITERATURE REVIEW

The literature review is presented in two sections. First, I discuss some of the early conceptualizations of WOM communication and link it to classic and contemporary perspectives of how marketing perceives WOM to be valuable. Then, I explain how some of more recent WOM forms marketing scholars have investigated and practitioners have leveraged (e.g., online WOM and incentivized WOM referrals) do not share the characteristics of classical WOM definitions. These missing characteristics challenge the theoretical rationale for why previous research has shown WOM to be more potent than advertising in changing consumer attitudes and behavior (Allsop et al. 2007; Brown and Reingen 1987). This review of the literature suggests that online and offline WOM operate differently in influencing consumer behavior. I also describe the theoretical rationale for why such new forms of WOM may still be potent (e.g., referral rewards programs), albeit for different reasons than traditional WOM.

Next, I continue to discuss the extant marketing literature that expressly focuses on the role of WOM on marketing outcomes. This section identifies and discusses literature that investigates individual-level (consumer-level) response to WOM and research that examines how aggregate levels of WOM influence marketing performance (e.g., sales, firm-level financial performance). Particular emphasis is placed on literature that has investigated how WOM influences brand-level marketing performance. In this section of the review, I discuss the role of personal and interpersonal factors (social ties) in the dissemination and influence of WOM communications on marketing outcomes. In particular, the extant marketing literature presents theoretical arguments and empirical evidence that supports the “strength of strong and weak ties

(Goldenberg et al. 2001; Granovetter 1973) in terms of WOM driving marketing performance. Researchers have used product life cycle, market characteristics, and product/service category factors to explain how and why weak or strong ties may be more effective than the other. During this review, I also discuss the various ways researchers have measured and operationalized WOM. Notably, a great deal of recent marketing literature linking WOM to marketing performance does not actually measure WOM but rather makes an assumption that an observable but non-WOM measure is a reasonable proxy for WOM activity.

Early Conceptualizations of WOM in Marketing

Arndt (1967, p. 191) defines WOM advertising as "oral, person-to-person communication between a perceived non-commercial communicator and a receiver concerning a brand, a product, or a service offered for sale," and Westbrook (1987, p. 261) defines it as "informal communications directed at other consumers about the ownership, usage, and characteristics of particular goods and services and/or their sellers." Early marketing literature incorporating WOM uses these perspectives as the formal WOM definitions of their studies (e.g., Bayus 1985; Higie et al. 1987; Lampert and Rosenberg 1975; Reingen and Kernan 1986). Early marketing practitioners and scholars were interested in WOM communication because of how its characteristics, and thus its impact on consumer behavior, differed from other forms of persuasive marketing communications. They considered it distinctive because of its (1) method of transmission and (2) how receivers interpret the motives of the communicator. , Prevailing explanations of why WOM tended to have a greater impact on changing consumers' attitude and behavior than marketing communications included the following: (1) WOM occurs face-to-face, (2) it is dynamic and adaptive, and (3) it does not seem to have overt commercial motives.

Unlike most marketing communications, WOM is direct and face-to-face. The dynamic and face-to-face nature of WOM is attributed as reasons for its potent influence for numerous reasons. WOM has been thought to be highly effective because of the inherent flexibility the messenger has in adapting the communication to accurately transmit the information or to counter resistances by the WOM receiver and face-to-face communication ensured nonverbal components of communication were transmitted as well (Rogers 1986). It is notable that the importance of this face-to-face component to aid in interpersonal influence is one of the enduring reasons why adaptive selling in personal selling situations is considered to be a particularly potent form of marketing persuasion (Weitz et al. 1986). Researchers have used media richness theory (MRT; Daft and Lengel 1986) to explain that face-to-face communication should be superior (to "leaner" channels such as written letters) for accurate communication transmission because it is superior at (1) reducing the uncertainty (absence of information) surrounding the meaning of a message and (2) reducing equivocality (uncertainty in interpretation of available information) during a communication transmission. Moreover, MRT posits that the rapid adaptability, nonverbal cues, and transmission of personality traits should made face-to-face communication the most accurate form of communication and, in turn, a fertile ground for interpersonal influence to occur.

In addition, the face-to-face nature of WOM means the sender can impose social control (intentionally or unintentionally) in the form of sanctions for noncompliance or rewards for compliance (Beckman 1967). Researchers have also suggested that the face-to-face nature of WOM facilitates vivid transmission of information compared with many other forms of marketing communications (e.g., print advertisements). Under certain conditions, research has shown the vividness of WOM to increase accessibility and, in turn, its influence on attitude and

behavior (Herr et al. 1991). Traditional WOM is also thought to have a greater impact than marketing communications because it is perceived as independent of the commercial motive driving the messenger of marketing communications (Godes et al. 2005). Thus, WOM is impactful because the source is unlikely to be judged as having a commercial ulterior motive. In addition, in general, people tend to consider personal sources more trustworthy and credible than commercial sources, and thus WOM tends to have greater impact because of the known propensity of trust/credibility to facilitate attitude/behavior change (Morgan and Hunt 1994).

Investigation of WOM Using Online Consumer Content

However, despite the often-assumed and in some contexts empirically validated importance of WOM in marketing, marketing research explicitly measuring WOM remains relatively scarce given the methodological difficulties associated with measuring and quantifying it on a large scale (Rust et al. 2004a). Thus, it is of little surprise that practitioners and researchers alike have flocked to investigating how consumer WOM occurring in online channels influences marketing outcomes. Access to consumer WOM using online platforms proved to be a watershed moment in the marketing investigation of WOM: Studying online WOM seems to overcome the methodological difficulties associated with studying traditional (i.e., offline) WOM. Online product review systems, online message boards, and other web-enabled platforms created permanent, freely accessible records about consumer sentiment organized into a coherent fashion readily adaptable to empirical analysis (Dellarocas 2003; Godes and Mayzlin 2004). Since the early 2000s, marketing literature has noted this potential goldmine, and there does not seem to be any loss of interest among marketing scholars (e.g., Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Duan et al. 2008; 2004; Mayzlin 2006; Riegner 2007; Shin et al. 2010; Zhu and Zhang 2010). However, it is notable that most online

WOM communications examined in recent marketing literature do not share many of the characteristics of offline WOM that that were identified as the source of offline WOM's potency. Table 1 presents how offline and online WOM compare across the mechanisms theorized to explain its powerful influence as a driver of consumer behavior. Next, I summarize and discuss some of the methodological decisions and characteristics associated with online WOM marketing research investigations.

Table 1: Comparison of Online and Offline Characteristics Driving Consumer Influence

WOM Characteristic Driving Influence	Likely Characteristic of an Offline WOM Communication?	Likely Characteristic of an Online WOM Communication?	Supporting Literature
Sender can adapt rapidly to receiver to ensure successful transmission	Yes	Depends on specific mode of online communication	(Daft and Lengel 1986)
Nonverbal cues and personality traits clarify message equivocality and increase mechanisms for meaning transmission	Yes	Depends on specific mode of online communication, but all modes face-to-face	(Rogers 1986)
Sender can rapidly administer social rewards for compliance or punishments for noncompliance	Yes	Depends on context of online communication	(Beckman 1967)
Face-to-face interaction facilitates vividness effect on memory accessibility	Yes	No	(Herr et al. 1991)
Source is judged to not have a commercial motive (unbiased information)	Very Likely (e.g. buzz agents, referral rewards)	Likely (e.g. buzz agents, referral rewards, advertisers posing as consumers)	(Godes et al. 2005)
Source is highly credible (quality information)	Possibly	Possibly	

Godes and Mayzlin (2004) investigate the use of online conversations in USENET communities to predict viewership of new television shows. The authors note the difficulty and costs associated with tapping into traditional (i.e., offline) WOM networks, which motivated their study using an alternative method to measure WOM. The authors note that their finding that online WOM (eWOM) is informative in explaining offline consumer decisions “supports the idea that at least some aspects of online WOM are proxies for overall WOM,” (p. 546), but they also note that “future research to understand better the relationships between WOM and sales across these worlds would be valuable” (p. 558) and that there is a need to compare the extent to which online WOM and traditional WOM are similar and different. Similarly, Liu (2006) investigates the pre- and post-release Internet buzz of movie releases and the impact on box office sales. Modeling both the volume and the valence of WOM in Yahoo Movies forums, Liu (p. 87) concludes by noting that “further research examining the difference between online user data and that in the physical world appears to have potential.”

Zhang et al. (2006) also examine online WOM. However, unlike Liu (2006), who uses content analysis of unstructured online movie discussion, Zhang et al. use structured ratings (1–5 star ratings). Thus, Zhang et al. make the assumption that structured quantitative ratings operate with equivalent, or similar, mechanisms to classic offline WOM. The researchers investigate the role of online user ratings in a diffusion model on predicting box office revenues, beyond typical forecasting models, which rely on weekend opening revenues. The findings indicate that valence of the evaluations is the strongest predictor, a different finding than Liu (2006) and Godes and Mayzlin (2004). This may be attributable to Dellarocas et al. (2006) using an explicit rater-supplied metric of valence and the other studies using content analysis methods to infer valence.

Chevalier and Mayzlin (2006) also use structured ratings from two large online retailers to investigate the effect of structured consumer ratings on online book sales. The authors find evidence that the qualitative consumer content accompanying the review ratings have an impact on subsequent sales. Using the character length of the responses as a rough proxy for a poster's enthusiasm—suggesting that longer posts are more nuanced and "read like 4.5-star reviews" (p. 350)—their interpretation of the findings suggests that valence of the online WOM and the enthusiasm proxy (character count) is unable to capture the full dimensions of how online WOM communications drive market performance.

Duan, Gu, and Whinston (2008) use a simultaneous equation system to account for the endogenous nature of WOM because WOM is theoretically expected to be both a driver and a consequence of market performance. Their dynamic model uses online structured consumer movie evaluations to explain future box office revenues while also accounting for time-invariant factors of the product (movie)—such as genre (product category) and critic ratings (third-party expert reviews)—and prior box office sales. They find that WOM volume has a strong direct effect on box office revenue and prior periods of WOM volume also have a positive but diminishing effect. Furthermore, they find that cumulative and current period average WOM valence do not have a direct effect on box office revenue but WOM valence has a direct effect on WOM volume. In other words, the researchers separated WOM volume and WOM valence as two distinct variables in the model. Thus, it is uncertain whether the role of WOM valence as an indirect effect would persist in contexts in which WOM valence is embedded inherently within the WOM transmission itself (e.g., person-to-person communication), rather than compartmentalized and separated, as is the case with structured online review websites.

Chen, Wang, and Xie (2011) examine the interplay between online consumer reviews and observational learning (consumers seeing what other consumers bought after viewing a particular camera) on digital camera sales for Amazon.com. The authors find that negative online reviews have a greater absolute effect than positive reviews on sales. They also find that positive observational learning increases sales but negative observational learning information does not harm product sales.

Across the studies of online WOM in marketing reviewed here, several important assumptions are made about WOM, and these implications have not been explicitly considered in any of the aforementioned literature. First, most of these studies capture transmitted electronic messages from consumers, but the authors assume that the messages are received by an audience. In other words, WOM impact on marketing outcomes is contingent on the consequence of WOM transmission, not the transmission itself. Similarly, when quantitative ratings transmitted about WOM are used as indicators of the valence of the message, again, the assumption is that the WOM transmitter's evaluation of the message sentiment is a suitable proxy for the recipients' assessment of the WOM sentiment.

Despite the distinctions between offline and online WOM and the research assumptions that tend to accompany most online WOM investigations in marketing research, the popularity of using online WOM as a means to examine WOM is certain. The next section contains a more extensive review of contemporary marketing research linking WOM (in its multitude of forms) to various measures of marketing performance.

Marketing Literature Linking WOM to Marketing Outcomes

Table 2 summarizes recent studies about WOM and marketing performance. Extant research has demonstrated that certain forms of WOM are linked to marketing performance, though the size and nature of the linkage varies. For example, Godes and Mayzlin (2004) identify a dynamic link between online chatter and television show ratings. Liu (2006) also examines online WOM and links it with box office revenues. Subsequently, Duan, Gu, and Whinston's (2008) study of structured online movie reviews shows that WOM valence seems to influence subsequent WOM volume, which in turn affects box office sales. These studies emphasize that the sheer volume of online buzz is a signal to subsequent marketplace performance of entertainment media.

Table 2: Summary of Recent Literature Linking WOM to Marketing Performance

Study	WOM Type*	WOM Channel	Study Type	WOM Measurement	WOM Valence	Tie Strength	WOM Consequences	Context
The current research	**O**	**Online and offline**	**Secondary data analysis**	**WOM received**	**Y**	**Y**	**Immediate consequences and brand equity**	**Nationally-representative sample of consumers 13+years of age, more than1,000 brands**
Zhu and Zhang (2010)	O	Online	Secondary data analysis	WOM proxy—review ratings	Y	N	Sales	Sales of 220 video games of varying popularity
Chen et al. (2011)	O	Online	Secondary data analysis / quasi-experiment	WOM proxy —review ratings	Y	N	Sales	Digital camera reviews on Amazon.com
Schmitt et al. (2011)	E	Not distinguished	Secondary data analysis	WOM Proxy - Customers Acquired via Referrals	referrals only	N	Observed Customer Value, CLV	9,814 German bank business-to-consumer customers
Berger et al. (2010)	O	Online	Secondary data analysis & experiments	WOM (online reviews)	Y	N	Sales, Purchase Intentions	Book sales online under conditions of high/low awareness
Godes and Mayzlin (2009)	E	Not distinguished	Field experiment	WOM sent	positive only	Y	Sales	1,000 consumers; one restaurant/brewery
Luo (2009)	O	Not distinguished	Secondary data analysis	WOM Proxy – U.S. Department of Transportation filed complaints	negative only	N	Stock Returns, Cash Flows, Stock Volatility	9 airlines
Trusov et al. (2009)	O	Online	Secondary data analysis	WOM sent (e-mail referrals)	e-mail referrals only	N	Customer Acquisition	one online social networking site
DeBruyn and Lillien (2008)	E	Online	Online field study	WOM sent (e-mail referrals)	e-mail referrals only	Y	Online Survey Completion	1,116 participants purportedly in an online "small world" study
Duan et al. (2008)	O	Online	Secondary data analysis	WOM proxy - review ratings	Y	N	Revenue	71 movies, 3 online movie review sites
Villanueva et al. (2008)	O	Not distinguished	Secondary data analysis	WOM proxy—self-reported acquisition channel, including: web links, news articles, and search engines as WOM	referrals only	N	Customer Lifetime Value	Web hosting company
Keiningham et al. (2007)	O	Not distinguished	Secondary data analysis	WOM intentions	Y	N	Revenue Growth Rate	21 firms (5 categories) from the Norwegian Customer Satisfaction Barometer
Kumar et al. (2010)	E	Not distinguished	Field study	WOM proxy —customers acquired by referrals	referrals only	N	Customer Acquisition	Telecom and retail stores
Ryu and Feick (2007)	E	Not distinguished	Experiment	WOM intentions	Y	Y	DV was Referral Likelihood	mp3 players and telecom service,
Wangenheim and Bayón (2007)	O	Not distinguished	Survey research	WOM received and WOM sent	positive referrals	N	Customer Switching	688 consumers of an energy provider and 416 B2B firms
Chevalier and Mayzlin (2006)	O	Online	Secondary data analysis	WOM proxy—review ratings	Y	N	Sales Rank	2387 books across two online retailers
Liu (2006)	O	Online	Secondary data analysis	WOM proxy—review ratings	Y	N	Revenue	40 movies, Yahoo Movies review
Morgan and Rego (2006)	O	Not distinguished	Secondary data analysis	WOM sent (number of positive and negative recommendations)	Y	N	Market Share, Tobin's Q, etc.	80 firms selected from ACSI
Godes and Mayzlin (2004)	O	Online	Secondary data analysis	WOM sent	Y	N	TV Ratings	41 TV Shows, 169 Usenet groups

Notes: E = engineered WOM, and O = organic WOM.

Relative Effect of Positive and Negative WOM on Marketing Outcomes

Luo (2009) finds that negative WOM is linked to the financial performance metrics of firms in the context of the airline industry. The author finds a significant delay (wear-in effects) between the occurrence of negative WOM and the peak impact on financial metrics, illustrating the dynamic relationship between WOM stock returns, cash flows, and stock volatilities. The study also suggests that there is an enduring adverse effect of negative WOM (wear-out effect) on financial metrics and that negative WOM may induce a "vicious cycle," whereby performance shortfalls result in managers unable to invest in necessary ways to mitigate future negative WOM.

Other studies have investigated the relative effect sizes of positive and negative WOM at length. The results are equivocal and seem to be contingent on the specified time horizon of WOM impact (immediate response vs. delayed responses), operationalization of WOM impact (attitudes vs. behaviors), existing knowledge and associations a WOM recipient has about the brand, and context of study (experimental, survey, or field study). Field studies indicate that negative WOM is more rare (East et al. 2007) but tends to have a greater impact. For example, Chevalier and Mayzlin (2006) report an asymmetrically large effect of negative online book reviews on sales even though positive WOM existed in much greater volume. Other studies have suggested that the relative impact of positive WOM on a consumer's purchase intention is contingent on the consumer's prior purchase probability (East et al. 2008). Experimental results suggest that negative WOM has greater impact when brand commitment is low and decision involvement is high (Ahluwalia 2002) and that reactance to valenced WOM can even occur if consumers are triggered to maintain self-determination (Fitzsimons and Lehmann 2004). Although many insights into WOM valence have been observed in controlled laboratory settings

(e.g., Ahluwalia 2002; East et al. 2008; Giese et al. 1996; Herr et al. 1991; Laczniak et al. 2001), impact on consumers is usually only linked to immediate attitude change and not marketplace behavior. Presumably this is because of the practical limitations of laboratory experiments. This has resulted in questions pertaining to the generalizability of such findings to the real world and whether immediate consumer attitude changes correspond to managerially significant insights into the WOM impact.

Not all studies have demonstrated differences in effect for positive and negative WOM. For example, in the Liu (2006) study that used online movie reviews of consumers to predict box office revenues, only volume of WOM was a significant predictor of weekly box office revenues. Valence of WOM activity was not significant, though Liu notes that the insignificant link between WOM valence and consumer behaviors (manifested in changes in box office revenue) may be because of the nature of the movie market (i.e., the relatively short duration of movies in the marketplace narrows the window for concrete attitudes to form and drive behaviors). Thus, mere awareness—which is expected to be driven solely by WOM occurrence (volume) and not necessarily WOM content (valence)—is expected to be the greater driver because relatively impulsive moviegoing is driven more by awareness. Liu suggests that the importance of WOM valence as a driver of consumer behavior may be conditional on characteristics of the product/service category.

WOM Dispersion Across Social Groups and Marketing Outcomes

Researchers have also linked how WOM disperses across consumer groups to marketing performance. Two factors—the strength of the social tie (strong/weak) and information characteristics (particularly the degree of moral hazard associated with information

transmission)—are relevant in understanding the dyadic process of WOM exchange. First, the social tie (degree of social distance) affects exchange (Clark et al. 1986; Granovetter 1973) and the transmission of information (Frenzen and Nakamoto 1993). Ceteris parabis, as the tie strength increases, so does the likelihood of potentially valuable WOM transmission—thus, the "strength of *strong* ties" (Brown and Reingen 1987). However, some research has shown that when the moral hazard associated with a given piece of information is low, a consumer will transmit information willingly to weak ties the same as they would be expected to with strong ties. Frenzen and Nakamoto (1993) provide the low hazard examples of (1) information about a new shampoo in a store and (2) information about a sales promotion that is available regardless of the number of people who reap the benefit of the promotion. Social tie strength within a dyad has also been examined for incentive-driven WOM (e.g., referral programs). Through a series of experiments, Ryu and Feick (2007) find that referral rewards only have a marginal positive impact on referral likelihood between strong ties, while rewards have a strong positive impact on referral likelihood between weak ties.

Godes and Mayzlin (2009) report that marketer-engineered WOM (buzz marketing) by noncustomers is more valuable to a restaurant chain than WOM by current, loyal customers. The researchers interpreted the stronger effect from noncustomer WOM as being consistent with the "strength of weak ties" hypothesis (Granovetter 1973); the researchers reasoned that noncustomer WOM activated awareness and interest among consumers previously unaware of the restaurant. In a similar vein, a study of telecom customers demonstrates that the customers who generated the most valuable paid referrals are different from the customers with the highest lifetime value (Kumar et al. 2010). Together, these findings, though specific to buzz marketing

campaigns, suggest that WOM from both customers and noncustomers influences marketing performance.

In addition, Dellarocas et al.'s (2007) study of online WOM influence on box office revenue identifies greater impact of WOM when ratings are more equally dispersed across genders, which they interpret as evidence validating the critical role of WOM as it spreads across heterogeneous groups. The authors' theoretical rationale for including gender dispersion as a predictor of future box office revenue was that WOM transmitted across genders would be indicative of movie awareness traveling across weakly connected social groups (e.g., gender dispersion for movie viewings and subsequent online WOM activity indicated WOM spreading quickly across weak social ties). Because of limitations in the online data used for the Dellarocas et al. (2007) box office revenue forecasting study, age and gender were the only variables that could be measured to assess population heterogeneity.

Psychological and Dispositional Characteristics Influencing WOM Outcomes

Researchers have also identified psychological factors as moderators of the link between WOM and marketing performance. For example, the expertise and similarity (homophily) of the WOM sender as perceived by the WOM receiver accentuates the positive link between WOM and customer switching in the context of a European energy provider (Wangenheim and Bayon 2007).

It is known that heterogeneity exists among consumers in their likelihood to send WOM, seek WOM, and be influenced by different forms of WOM. Wangenheim (2007) notes that prior empirical results regarding linking satisfaction to WOM (e.g., Anderson 1998) have observed that consumers with the same level of satisfaction have greatly different WOM transmission

levels. He suggests that dispositional characteristics moderating the satisfaction → WOM link are a partial explanation for these prior findings. Wangenheim finds partial or full support for these dispositional moderators in a study of 416 consumers and 688 businesses in the European energy market. For example, consumers who displayed a greater degree of enduring marketplace involvement—market mavens (Feick and Price 1987)—were more likely to transmit WOM as satisfaction levels increase. The same study also found positive moderating effects for product and situational involvement on the relationship between satisfaction and likelihood of WOM transmission. Opinion leaders have also been commonly identified as people of a given product class who are more knowledgeable, involved, and likely to transmit WOM about products and brands within the product class (Childers 1986), and recent research has identified opinion leadership among high-volume Internet users (Lyons and Henderson 2005).

Another study identifies a consumer's need for uniqueness as a factor that determines the likelihood of WOM transmission for privately consumed products (Cheema and Kaikati 2010). The experimental study demonstrates that consumers high in need for uniqueness were less likely to transmit positive WOM about a publicly consumed product they bought or intended to buy because it threatens to undermine the uniqueness of their possessions. These findings suggest that marketers of publicly consumed brands with a relatively high concentration of high need for uniqueness customers may observe a shortage of positive WOM recommendations.

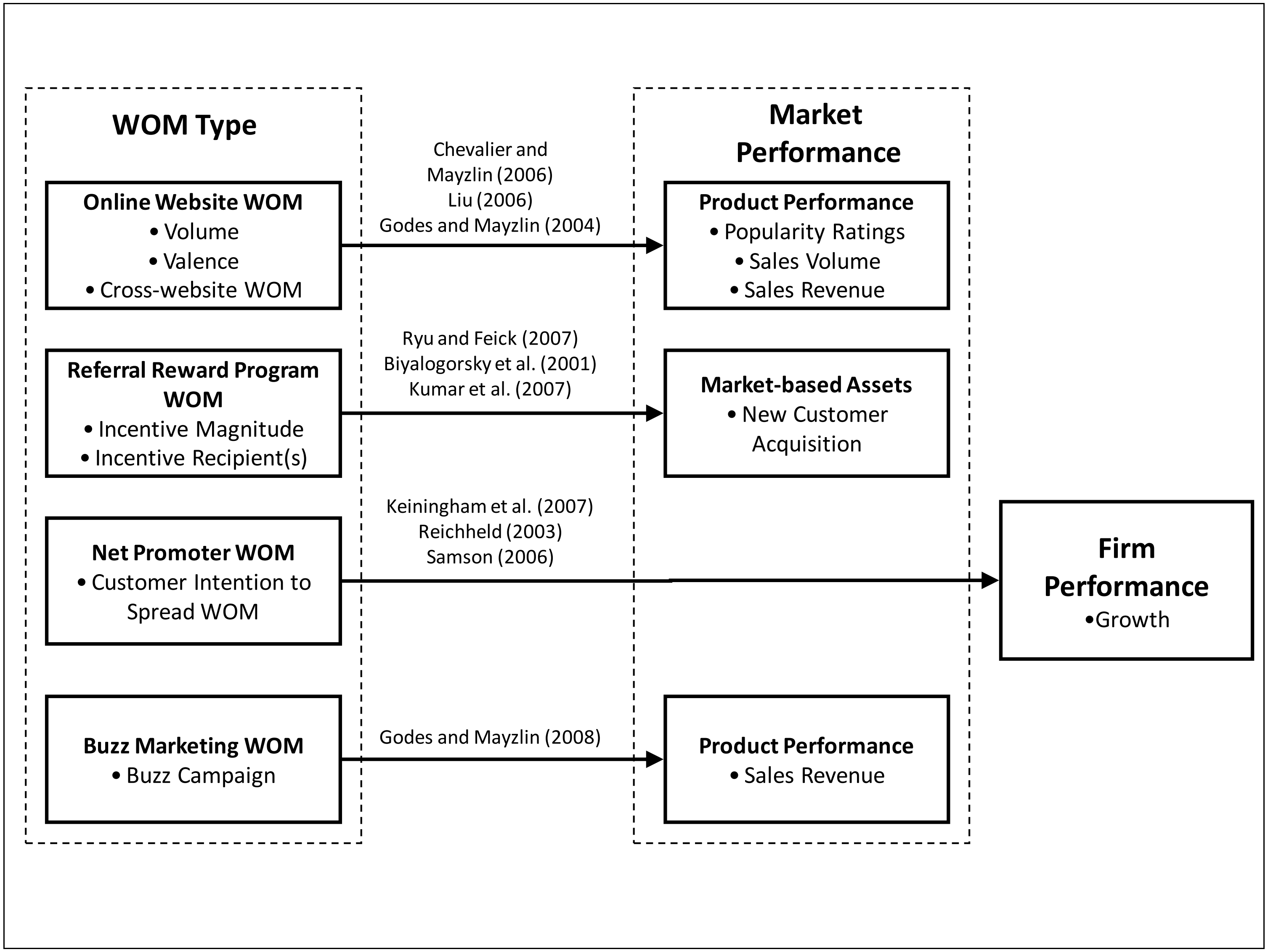
Methodological Factors in Studies of the WOM/Marketing Performance Link

Methodological factors may also affect the strength of the WOM and marketing performance link. A meta-analysis of WOM drivers demonstrates that methodological factors

strongly moderate antecedent relationships with WOM (de Matos and Rossi 2008); it is possible that methodological factors also moderate WOM consequences. In this portion of the review, I focus on how WOM is operationalized in a particular study and its implications on assessing marketing outcomes.

Figure 1 presents four prominent forms of WOM linked to marketing performance and representative studies: (1) Online WOM, (2) WOM driven by referral programs, (3) Net promoter score (WOM), and (4) WOM artificially generated (buzz marketing). Each of these types of studies and their implications and limitations are discussed subsequently.

Figure 1: WOM Forms Examined and Linked to Market and Firm Performance



WOM Operationalized as Online Reviews

First, WOM research emphasizes the analysis of WOM in online contexts to the exclusion of offline WOM (e.g., Godes and Mayzlin 2004; Trusov et al. 2009). These studies have focused on online WOM, such as Yahoo Movie Groups (Liu 2006), Amazon.com (Chevalier and Mayzlin 2006), or Usenet newsgroups (Godes and Mayzlin 2004). Naturally occurring online WOM differs from offline WOM because online WOM is not face-to-face and is often presented in a highly structured format (Dellarocas 2003); thus, there is uncertainty whether empirical findings between online WOM and product sales translate to offline WOM.

Because online reviews are sticky (i.e., they persist well after the initial transmission) and organized (WOM data is usually systematically organized in some manner by the system), online reviews inherently overcome two of the primary challenges in collecting offline WOM, thus making it appealing to researchers. The literature stream (discussed extensively in previous portions of this literature review) that has investigated how online consumer movie reviews impact box office forecasting models is a prominent example of this type of measurement approach (Duan et al. 2008; Liu 2006; Zhang et al. 2006), though examples of using online WOM exist in other product/service categories as well (e.g., book sales [Chevalier and Mayzlin 2006] and television ratings [Godes and Mayzlin 2004]).

Word of mouth measured in this way tends to exhibit particular characteristics. For example, because the WOM data are collected from persistent online source (e.g., message boards, discussion groups, customer review sites), measures of the valence of the WOM communication is sometimes available in a structured form (e.g., the five-star rating system of Amazon.com), or the valence of WOM communication is inferred through content analysis of the collected WOM messages (in that case, a structured valence response is unavailable). In

addition, because transmitters of online WOM are behind a digital veil, limited information about the characteristics of the WOM sender is available. (In the case of the movie forecasting studies using Yahoo! MovieGroups, age and gender of the WOM sender were available.) In addition, WOM data measured this way must assume that sending WOM is equivalent to reception of WOM, because online posted WOM communications only ensures that WOM transmission was attempted, not necessarily received by others. In turn, online WOM measured in this manner cannot capture actual dyad characteristics of a WOM exchange.

WOM Operationalized as Incentivized Referral

Other studies have investigated how incentivized referral activity (engineered WOM rather than organic WOM) affects sales and customer acquisition (e.g., Biyalogorsky et al. 2001; Kumar et al. 2010; Ryu and Feick 2007; Schmitt et al. 2011; Wangenheim and Bayon 2007). Research in this area has investigated the marketing (brand strength, incentive size) and sociological factors (tie strength) that drive referral likelihood in referral reward programs (Ryu and Feick 2007). Other research has attempted to model how different marketing investments, including referral incentives, impact referral activity. For example, Biyalogorsky et al. (2001) presents a model that portrays the balance of price reductions and referral incentives depending on customers' delight (extreme satisfaction) threshold. In addition, by identifying and marketing to current poor referrers and incentivizing them to generate more profitable new customer acquisitions, Kumar et al. (2007) note drastic improvements on marketing return on investment. This stream of research has demonstrated the utility of referral reward programs to generate beneficial WOM, but questions remain as to whether "customers-as-commissioned-sales force" WOM operates and affects customer acquisition and retention in the same manner as offline natural WOM. In other words, these studies demonstrate that beneficial WOM can be

engineered through incentives but are not are not designed to address how organic WOM drives marketing performance.

An advantage of investigating incentivized referral programs is that, from a data collection perspective, the programs are designed to explicitly account for WOM impact. Newly acquired customers who were motivated in part by a referee will report the WOM referral behavior, thus allowing firms to easily assess the extent of successful WOM communications (Ryu and Feick 2007). However, this method is constrained to observing only a portion of the WOM spectrum: referral WOM that was successful in acquiring a new customer.

WOM Operationalized as Net Promoter Score

Net promoter score (NPS) is a metric derived from customer response to a recommendation likelihood question; the NPS score is derived from the proportion of customers with a high recommendation likelihood rating minus the customers with a moderate to poor recommendation likelihood rating. Thus, use of NPS metrics to link WOM to market performance focuses solely on one form of WOM: consumer-to-consumer referrals motivated by consumption experience. Although Net Promoter is popular in industry use (Creamer 2006), recent empirical results by Keiningham et al. (2007) conclude that Net Promoter is not the best sole indicator of firm growth. With regard to Net Promoter being the best predictor of firm growth, Keiningham et al. (p. 45) conclude that “our research suggests that such presumptions are erroneous. The consequences are the potential misallocation of resources as a function of erroneous strategies guided by Net Promoter on firm performance, company value, and shareholder wealth.” Thus, although Net Promoter is a metric that captures some elements of WOM activity (albeit intentions, not actual behavior) and links them to one aspect of firm performance (growth), the theoretical debate and equivocal empirical findings suggest that Net

Promoter has not provided a complete picture of the WOM → performance link. For example, in one study, Samson (2006) found that including actual negative WOM with Net Promoter had greater efficacy on predicting changes to revenue growth of firms. The survey-based NPS approach is probably the most popular example of how WOM intentions are used as a surrogate measure of actual WOM behavior. The NPS approach of measuring a customer's likelihood of recommending the product/brand/service to others illustrates the simplicity of measuring WOM intentions in that simple survey-based research methods can easily measure intention to send any form of WOM. Although NPS is heavily used in marketing practice, some practitioners have noted the limitations of using WOM intention as a surrogate for actual WOM behavior (Kirby and Samson 2008).

WOM Operationalized as Engineered WOM (Buzz Marketing)

Godes and Mayzlin (2009) demonstrate a positive empirical link between WOM marketing campaigns (dubbed "exogenous WOM") and a positive impact on sales. This extends prior empirical findings that have linked WOM naturally created as result of consumer's experiences with the product ("endogenous WOM") with sales performance. In their study of a WOM marketing campaign using two populations—loyal customers and noncustomers (recruited through a consumer panel)—the researchers find evidence that noncustomer WOM activity generated greater value for the firm than WOM generated by current, loyal customers. These findings suggest that the most loyal customers generate firm value through their own actions (purchase), while less loyal customers can generate significant value as well (new customer acquisition). The authors argue that the results provide empirical evidence than WOM can, to some extent, be managed.

Other research in this area has demonstrated that buzz marketing cannot merely assume that consumer WOM generated from buzz marketing activities will parrot the marketer's desired message. Research into online social networks has shown that marketers' efforts to manage consumer WOM is strongly controlled and reinterpreted through consumer communities (Kozinets et al. 2010). The implication is that any WOM measurement of buzz marketing activities must quantify the actual content of any consumer-generated WOM because the marketers' assumed message may be appropriated, modified, or redefined over time.

Other Operationalizations of WOM

Another tendency in WOM research is the frequent use of WOM proxies. Moreover, it is common not to measure WOM at all and instead merely assume that relationships between two measured marketing variables are partly explainable by a presumed WOM process occurring. This tendency to use proxies or avoid measurement of WOM directly is not surprising; marketers have long lamented that measuring the extent of its impact is impractical, imprecise, or both. Sandage's (1948) advertising textbook claims that measuring the impact of WOM is impossible. The challenges of empirically quantifying WOM impact continues to echo in current marketing literature as well. For example, Zeithaml (2000) asks how WOM from retained customers can be quantified and names it an important research stream to pursue for understanding the consequences of service quality investments. In addition, despite WOM being conceptually recognized as an essential antecedent to revenue and profits due to new customer acquisition (Rust, Ambler, et al. 2004 ; Rust, Lemon, et al. 2004), it is rarely empirically modeled (Kamakura et al. 2002). Examples of studies using WOM proxies include Luo (2009) using consumer complaints filed with the U.S. Department of Transportation as a proxy for negative WOM. Arguably, Chevalier and Mayzlin (2006) using solely the quantified online product

review ratings is also a proxy for WOM volume and valence, and NPS researchers using a referral likelihood intention index measures are using an intention measure as a surrogate for positive WOM referrals (Reichheld 2003).

WOM Not Operationalized (Implied WOM)

Another approach to measuring WOM is to not actually measure it at all and instead make a theoretical argument that certain parameters in predictive models represent (at least in part) WOM effects. Perhaps the best example of this is the work on new product diffusion models (Sultan, Farley, and Lehmann 1990). For example, the Bass model "coefficient of imitation" (Bass 2004) is intended to partly capture the WOM effects that influence consumers to adopt a new product.

In all of the discussed methods of measuring WOM, compromises in the WOM data are made either in terms of (1) the WOM context, (2) the WOM type, (3) the richness of the WOM dimensions, or (4) the actual WOM behavior observed. If the intent is to generalize the findings of a study to a broader array of WOM contexts and types, these approaches must assume that their measured form of WOM operates the same as organic WOM. In summary, research that has explicitly studied the relationship between WOM and market performance has primarily examined WOM intention (rather than actual WOM), online WOM (rather than offline WOM), and incentive-driven WOM (rather than organic WOM). Thus, the brunt of research on firm performance implications of WOM activity does not contain the properties of WOM traditionally defined by Arndt (1967) and subsequently by Stern (1994): real-life exchanges of ephemeral oral or spoken messages. This is a distinct gap in the current marketing/firm performance literature

because the very reason WOM is noted to be particularly persuasive and influential is theorized to be embedded in the properties highlighted in these classic definitions (noncommercial, personal, real-life exchange). Thus, although the current marketing literature has made important contributions linking forms of WOM to market performance, the question remains whether these links persist in the same functional manner (and to what degree) when organic, offline WOM is the variable of interest. In addition, much of the prior empirical literature summarized previously focuses only on the WOM–performance relationship in terms of positive WOM, even though some empirical findings have found that negative WOM is a stronger predictor of decreases in firm revenue than positive WOM having a positive effect on revenue (Ferguson 2005). Thus, any further research investigating the effect of WOM on firm performance should account simultaneously for both the positive and the negative effects of positive WOM and negative WOM, respectively. "With fundamental differences between online and offline SIs [social interactions] (e.g., anonymity and speed of diffusion) understanding the relationship between these two forms of SIs is a fertile research area" (Godes et al. 2005, p. 420). In the next section of this review, I discuss how literature has theorized and empirically linked marketing tactics to WOM generation and, subsequently, how it ultimately generates new customer acquisition.

Studies of WOM Forms and the Impact on Customer Acquisition

Prior research has emphasized the role of WOM in the diffusion of innovations and market knowledge (Frenzen and Nakamoto 1993). This literature suggests that one critical way WOM may affect brand performance is through the acquisition of new customers who were

made aware of the brand and/or new customers who were aware of the brand but developed sufficiently positive brand associations to become a customer.

Current literature has examined distinct forms of WOM and how the type of WOM affects the acquisition of new customers. Three primary WOM forms have been investigated: (1) WOM motivated by personal consumption experiences (Luo and Homburg 2007; Wangenheim and Bayon 2007) and (2) WOM motivated by marketing incentives (e.g., referral programs) (Kumar et al. 2010; Ryu and Feick 2007; Schmitt et al. 2011). Less investigated is (3) the link between WOM and customer acquisition when WOM is not linked to an actual consumption experience (e.g. viral/ buzz marketing). Although all three forms of WOM can lead to new customer acquisition, we distinguish each as a unique WOM channel because different acquisition processes have substantial consequences on retention probability (Thomas 2001) and value creation (Lewis 2006). Throughout this discussion, I focus attention on how particular firm-controllable factors may drive WOM.

(1) Consumption-Driven WOM → Customer Acquisition.

Models linking service quality and customer satisfaction to firm performance have long postulated that the critical process linking the two variables is partly that highly satisfied customers deliver positive WOM and thus recruit additional customers to a firm essentially for free (Anderson and Mittal 2000; Rust et al. 1995). Positive WOM sent because of personal experience with a brand is likely to induce many positive brand associations in the WOM receiver because the WOM message likely conveys functional, experiential, and symbolic benefits of the brand. A great deal of research has emphasized that personal consumption experiences are a key trigger of WOM activity (Anderson 1998; Anderson and Mittal 2000; Swan and Oliver 1989; Westbrook 1987). However, it has been argued that the link between

satisfaction and WOM should not be presumed to be a simple positive relationship. Although satisfaction also positively affects loyalty and reduces defection likelihood, Biyalogorsky (2001, p. 84) notes that “converging evidence suggests that customer behavior changes once a threshold has been passed, leading to… intention to spread WOM.” Biyalogorsky and others theorize that satisfaction-driven WOM occurs at distinct thresholds of satisfaction: “Delight” triggers positive WOM, while a certain negative satisfaction threshold triggers negative WOM (thus inhibiting new customer acquisition).

Hogan et al. (2003) find that the WOM-based value (compared with value due to actual purchases) of a customer was particularly powerful in the early stages of the product life cycle because of the future customers acquired through WOM activity. In a longitudinal study of 139 firms using several secondary databases, Luo and Homburg (2007) find a positive empirical link between customer satisfaction investments and the efficiency of subsequent advertising. The authors suggest that this link can be explained by the free advertising of positive WOM generated by satisfied customers (thus complementing subsequent marketing communication investments) and therefore that future marketing investments are more efficient at acquiring customers because of the supporting satisfaction-driven WOM activity. However, the authors were not able to assess an actual empirical link between WOM and marketing efficiency because of data limitations in the secondary data sources.

(2) Incentive-Driven WOM → Customer Acquisition

Formal customer referral programs are emerging as popular tools for marketing managers to actively manage customer WOM (Ryu and Feick 2007). Referral programs are considered a potentially valuable CRM tool because they can attract new customers and can improve retention of current customers through rewards. For example, Kumar et al. (2010) illustrate that customers

with the highest lifetime referral value are not necessarily those who have the highest lifetime value (cash flows due to purchases only), and a tailored referral reward marketing campaign positively influenced lifetime referral value of customers.

Biyalogorsky et al. (2001) model when referral reward programs are most efficient at driving referral activity. Drawing on theory that customers behave drastically differently when they cross a delight threshold, their model suggests that referral reward programs are best suited when consumers' threshold for delight experiences are moderate (driving incentive-driven WOM); the authors recommend price reductions as the preferred strategy to induce referral activity (driving organic WOM) when the threshold for customer delight is low. Their model posits that organic WOM can be generated by lowering price but may be inefficient or even have negative firm performance relative to referral programs because free riders will reap the benefits of lower price but not generate WOM. However, there was no empirical application or test of the proposed model.

Some evidence also suggests that customers acquired through incentivized referral are more valuable to firms than customers acquired through traditional marketing means. Schmitt, Skiera, and Van den Bulte (2011) tracked more than 5,000 customers acquired by a German banks' incentivized referral program and compared the short- and long-term value of these customers with 4,633 nonreferred customers (noting that some of these customers may have be recruited through organic WOM). After controlling for demographic characteristics, both the short- and long-term contribution margins and retention rates of referred customers were higher on average. The results also indicate that different demographic groups of referred customers were significantly different in terms of their relative CLV than equivalent nonreferred acquired customers.

(3) Buzz-Driven WOM → Customer Acquisition

Marketers have increasingly emphasized the role of marketing communications in generating WOM, rather than directly influencing purchase per se. Buzz marketing communications are meant to drive new customer acquisition primarily in an indirect manner: through the mediated effect of WOM activity.

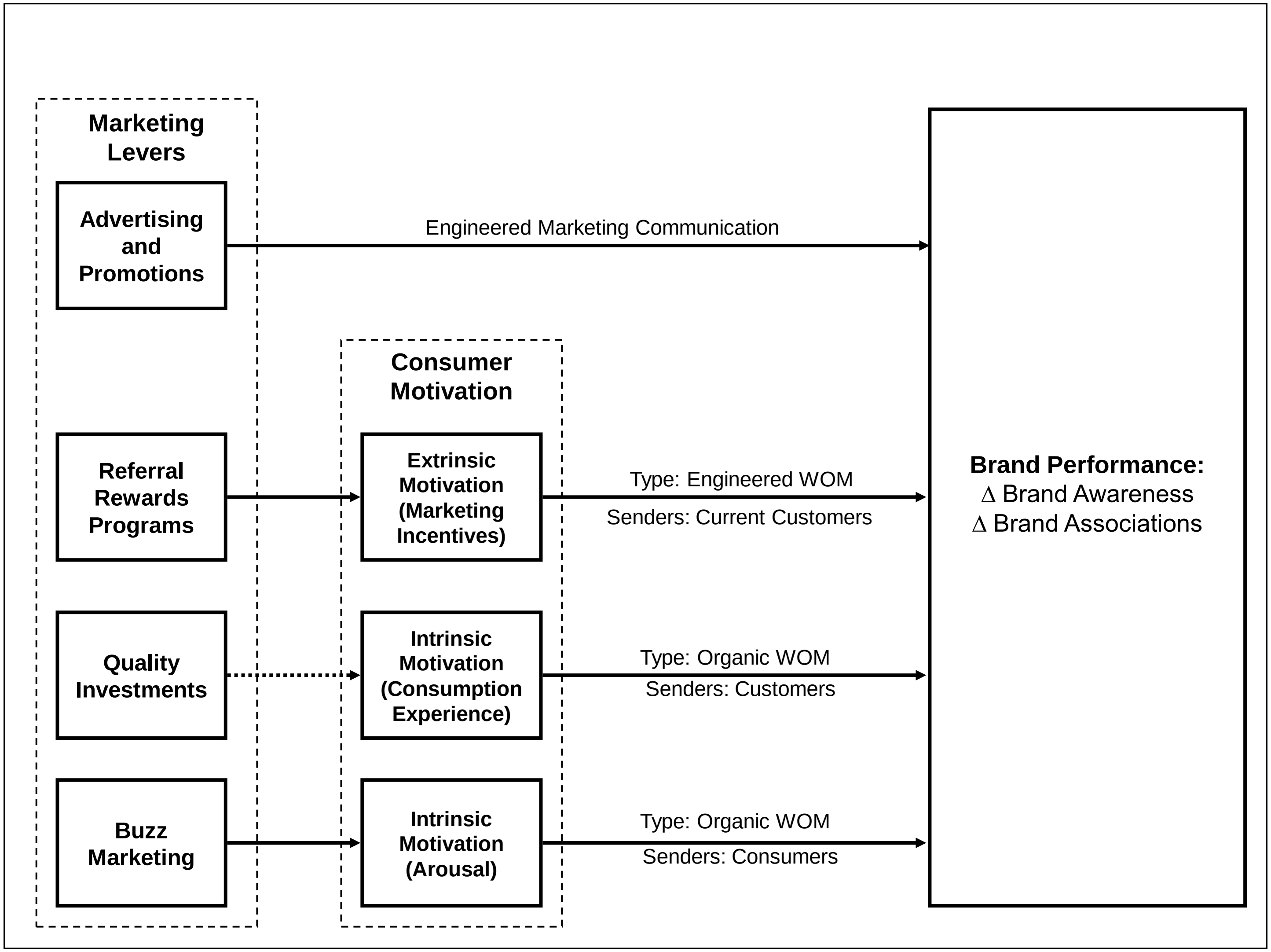
Although buzz marketing has been heralded as a potentially powerful form of marketing communication, there is relatively less evidence of how buzz-driven WOM affects market performance in the long run. Instead, current research has primarily focused on understanding the marketing tactics and situational factors that drive the volume, duration, and valence of buzz-driven WOM (Nail 2007). A notable exception is Godes and Mayzlin (2009); their findings suggest that buzz marketing campaigns have the most beneficial effect on sales performance through new customer acquisition when the campaign generates buzz and advocacy among nonloyal customers rather than highly loyal and satisfied current customers. The authors' rationale is that buzz campaigns are wasted on current, loyal customers because they have likely already engaged in evangelism for the company (consumption-driven WOM). However, the Godes and Mayzlin study did provide small incentives for the nonloyal customers contingent on their WOM generation; thus, there is some uncertainty whether their findings can be appropriately understood as reflecting who (nonloyals) are most likely to drive new customer acquisitions as the result of nonincentivized buzz marketing campaigns.

Although buzz marketing is intended to generate natural WOM, another consequence (intentional or unintentional) of some buzz campaigns is the generation of consumer-generated

media. This media includes online forum postings, social networking site posts, and blog posts (Nielson BuzzMetrics) and has been linked to subsequent increases in sales volume of consumer-packaged goods (Niederhoffer et al. 2007).

Figure 2 summarizes the three routes of WOM activity leading to customer acquisition. Included in the figure is the classical advertising and promotions logic to new customer acquisition (i.e., that it is not mediated through WOM activity) to demonstrate the distinct contrast from the WOM-mediated routes to customer acquisition. Although WOM activity is generated in all three cases, they are all distinct in terms of (1) the types of marketing investments expected to generate the WOM, (2) whether the marketing investment is primarily intended to generate WOM or is just one ancillary outcome of the marketing investment (e.g., the dotted line linking quality investments to WOM), (3) whether the consumer is intrinsically or extrinsically motivated to send WOM (distinguishing engineered WOM from organic WOM), and (4) whether customers or any consumer is expected to generate the WOM. This figure clarifies some of the primary differences between the WOM channels.

Figure 2: Summary of Investigated Links of Marketing Efforts on Brand Performance Through WOM Effects



CHAPTER 2: CONCEPTUAL OVERVIEW – LINKING WOM TO BRAND PERFORMANCE USING THE BRAND EQUITY FRAMEWORK

Marketing literature on brand equity suggests that the relationship between WOM activity and brand performance can be understood through the impact WOM has on the brand knowledge of potential and current customers. Keller's (1993) conceptual model of customer-based brand equity posits that customer-based brand equity can be understood as an associative network memory model driven by brand awareness and brand associations. Keller (p. 2) argues that "a firm's most valuable asset for improving marketing productivity is the knowledge that has been created about the brand in consumers' minds from the firm's investment in previous marketing programs." This conceptualization of brand equity emphasizes that short-term marketing actions can have long-term consequences on marketing productivity and consumer behavior because all future consumer interactions with brand information are cast through the lens of existing brand knowledge structures. This conceptualization of brand equity also makes clear that brand awareness and associations may come from orchestrated marketing communications but likely also come from sources outside the firm, such as consumer WOM communications.

From this perspective, the theoretical link between WOM and brand performance is twofold: through WOM's impact on brand awareness and brand associations. Closely related is Godes and Mayzlin's (2009) conclusion that a WOM campaign can affect awareness and/or preference. First, WOM can create (or strengthen) brand awareness among potential customers of a brand. Absent any particular type of brand associations successfully transmitted in a particular WOM episode, WOM-driven brand awareness may be sufficient to motivate consumer

actions toward the brand. In the case of low-involvement contexts (Petty et al. 1983) or situations of low consumer motivation, opportunity, or ability (MacInnis et al. 1991) to distinguish market offerings, brand awareness may be sufficient to motivate purchase. Alternatively, WOM-driven brand awareness may simply motivate a potential customer to seek additional information or be attentive to future incoming brand information (whether from a media source or other WOM). In most cases, however, brand awareness is a necessary precursor to creating brand associations in the minds of potential or current customers. It is the associations made about a brand that drive brand equity because brand equity is the differential effect consumers have toward marketing efforts solely because of the brand signal.

Second, WOM communications can affect the brand associations in consumers' memory. Indeed, WOM communications may have strong efficacy in creating brand associations in consumers' minds because the WOM communicator not only sends the specific content of the message but also inherently transmits non-product-related attributes such as (1) the type of people who use (or do not use) the brand, (2) symbolic benefits of the brand (e.g., social approval of prestige for use or nonuse of the brand), and/or (3) information about the personality of the brand through transference of a prototypical consumer's personality (Aaker 1997; McCracken 1989) because of the WOM receiver's perceptions of the WOM transmitter him- or herself. Such signals have been identified as less tangible but particularly powerful sources of brand knowledge for consumers, because they are unique points of differentiation difficult for competitors to imitate (compared with tangible attributes) and can lead to brand resonance (Keller 2001). Combined with WOM's relatively higher level of credibility and trustworthiness compared with marketing communications (Nielsen Consumer Research 2009), WOM can alter brand associations and the resulting consumer behavior.

Furthermore, this model suggests both customer and noncustomer WOM can influence responses to brands and that brand-related WOM is also an outcome of customer-based brand equity (because WOM is one possible behavior resulting from altered brand knowledge).

In summary, this customer-based brand equity framework is thus a marketing and brand-focused model that is consistent with more general frameworks of communication theories and human learning. Interpersonal communication frameworks are grounded in the principle that one's change in knowledge (i.e., awareness/attitude) is an outcome of an interactive process dependent on the characteristics of the message source, the message recipient, the message itself, and the mechanism used to transmit the message (Barnlund 1970; Duncan and Moriarty 1998).

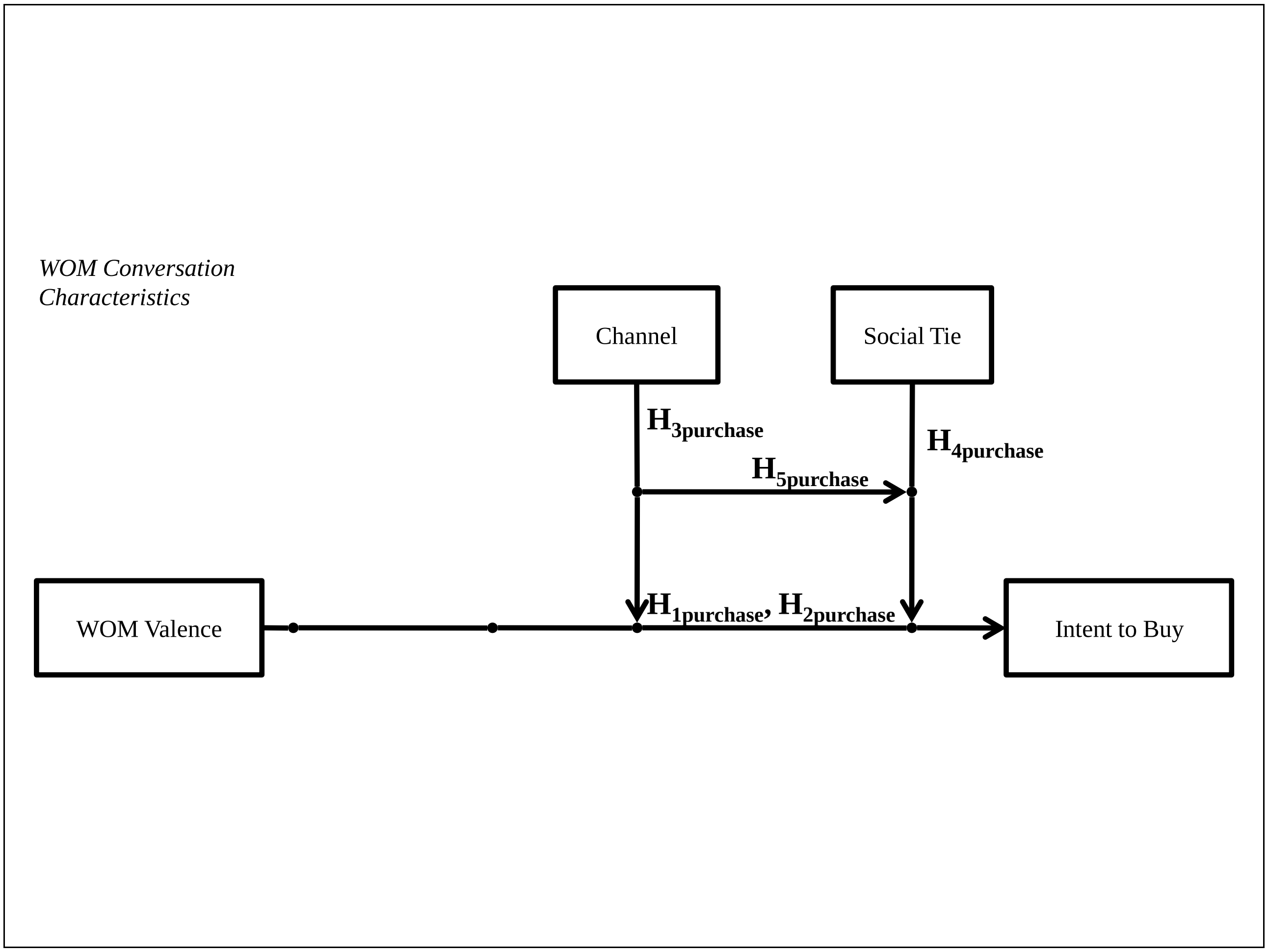
This dissertation uses customer-based brand equity as a general framework for all the research hypotheses, and I employ communication, psychological, and sociological theories to explain the processes that should result in differential WOM effects. These effects constitute the research hypotheses generated for Investigation 1. Investigation 1 thus focuses on hypotheses regarding micro-level brand performance (consumer-level response) of WOM—the purchase intentions of the WOM recipient and the recipient's intentions to retransmit the WOM message as well as seek additional information. Investigation 2 considers how these micro-level phenomena are further influenced by aggregate properties of a particular brand.

CHAPTER 3: INVESTIGATION 1: HOW WOM CHARACTERISTICS AFFECT CONSUMERS' BRAND BEHAVIORS

Hypotheses for Investigation 1: Purchase Intentions

Figure 3 depicts the model to be tested for how individual WOM episodes are expected to affect consumers' immediate behavioral response. Table 3 summarizes theoretical rational, which I discuss in greater detail next. All else being equal, the behavioral intention of a WOM recipient is expected to align with the valence of the received WOM about a brand.

Figure 3: Conceptual Model: Purchase Intentions



Although researchers have observed that a consumer may engage in reactance to WOM if his or her need to maintain self-determination is triggered (Fitzsimons and Lehmann 2004), the expectation remains that in most real world settings, it is unlikely that there is sufficient impetus to engage in reactance. Furthermore, in general, negative WOM should tend to have an asymmetrically greater effect on behavioral intentions than positive WOM. Again, in real-world settings, positive WOM tends to dominate the landscape (Keller 2007), and thus a novelty effect from negative WOM can partly explain its greater influence on judgment and behavior (Fiske 1980). Moreover, behavioral economics and social psychology studies have observed a strong loss aversion tendency in consumers (Tversky and Kahneman 1991), and this explanation further suggests that in the real world, negative WOM will tend to have an asymmetrically greater effect.

$H_{1purchase}$: Positive WOM has a positive influence on purchase intentions, and negative WOM has a negative effect.

$H_{2purchase}$: Negative WOM has a greater absolute effect on purchase intentions than positive WOM.

The channel of WOM communication may also affect WOM impact. Media richness theory suggests characteristics of different transmission mediums are reasons offline and online WOM may differentially alter brand knowledge structures (Daft and Lengel 1986). The theory also suggests that offline communication should be superior to online forms of communication in terms of delivering accurate messages because of rapid communicator adaptability, nonverbal cues, and easy transmission of personality traits afforded by rich face-to-face transmissions compared with most online mediums. Indeed, scholars investigating the emergence of decentralized computer-based interpersonal interactions have noted that though such interpersonal communication could be interactive just as face-to-face communication is and thus

distinct from one-way mass media messages, the more often limited scope of the "nonverbal band" of communication, the potentially asynchronous nature of communication, and the less rich socioemotional content across such a channel (Rogers 1986, pg. 26) implies that how people would be influenced by online interpersonal communication should be measurably distinct when compared with offline communications. Because in general offline WOM should be able to send more accurate brand communications and associations, offline WOM communication should have a greater impact on a WOM recipient's purchase intention than online WOM communication.

> **$H_{3purchase}$:** The effect of positive or negative WOM is accentuated when the conversation occurs offline rather than online.

Furthermore, the social tie strength should affect the absolute effect of brand-related WOM. It is known that the social tie (degree of social distance) affects exchange (Clark et al. 1986; Granovetter 1983) and information transmission (Frenzen and Nakamoto 1993). As tie strength increases, so does the likelihood of tailored, relevant, and personalized WOM transmission. This is characterized as "the strength of *strong* ties" (Brown and Reingen 1987). However, when network effects of WOM are considered, researchers have suggested that information transmitted between strong ties will tend to quickly become redundant because it propagates within a relatively small and closed network. Thus, information exchanged between weak social ties has more impact because the information will tend to be novel and eventually propagate through a new social network. This is known as the "strength of weak ties." In terms of immediate WOM outcomes such as purchase intentions, the strength of strong ties effect should persist, meaning a WOM recipient will be more likely to take action from received WOM

from strong ties because of a generally higher level of trust in the WOM sender, generally higher level of homophily among strong ties (McPherson et al. 2003), and more tailored WOM advice.

In addition, previous research has observed that strong social ties tend to exhibit higher levels of demographic and perceptual homophily, or the degree of congruence between a social dyad. Gilly et al. (1998) investigate how demographic and perceptual homophily influences WOM impact when consumers are actively searching out product information from others. When the authors controlled for each form of homophily, perceptual homophily had a positive main effect. This provides further evidence that brand purchase intentions effects based on WOM recommendations received from strong ties should be accentuated when the conversation is between strong social ties.

Moreover, because many of the intangible forms of brand associations from WOM information that can be sent by strong ties are contingent on a sufficiently rich channel to convey it, communications offline between strong social tiers should have the most influence of all. In contrast, online communications between weak social ties may be even less impactful because consumers have been shown to be somewhat more suspicious of WOM information from sources online that are not well known (Godes et al. 2005).

$H_{4purchase}$: The effect of positive or negative WOM on purchase intentions is accentuated when the conversation is between strong social ties rather than weak social ties.

$H_{5purchase}$: The effect of positive or negative WOM on purchase intentions is accentuated even further when it is between strong social ties in offline channels.

These hypotheses suggest that the relative influence of a WOM conversation about a brand on purchase intentions is influenced heavily by the WOM valence, the social tie, and the channel. Table 3 summarizes the research hypotheses.

Table 3: Hypotheses Summary: Purchase Intentions

WOM Characteristic	Hypothesis	Reasoning	Supporting Literature
Valence	$H_{1purchase}$: Positive WOM has a positive influence on purchase intentions and negative WOM has a negative effect.	WOM valence triggers matching buy/try intentions: WOM is generally considered one of the most informative and influential sources of information for consumer decision making, and behavioral intentions tend to align with WOM sentiment.	Berger and Milkman (2010); Mittal, Ross, and Baldasare (1998); Brown, Homer, and Inman (1998); Shin, Hanssens, and Gajula (2010)
	$H_{2purchase}$: Negative WOM has a greater absolute effect on purchase intentions than positive WOM.	The tendency for negative information to have an asymmetrically greater effect is well-founded in other marketing domains (e.g., advertising, product-attribute judgments, service performance) and is consistent with risk-averse behaviors predicted by prospect theory.	
Valence × Channel	$H_{3purchase}$: The effect of positive or negative WOM is accentuated when the conversation occurs offline rather than online.	Offline WOM tends to influence buy/try intentions more strongly: Comparatively lean online channels of communication may tend to obscure the transmission of important forms of brand value, such as user and usage imagery or experiential and symbolic benefits. Thus, richer channels such as face-to-face (offline) WOM should motivate purchase behavior because of its ability to transmit a more complete picture of brand value and reduce uncertainty/ambiguity surrounding the information.	Keller (1993), Daft and Lengel (1986), Rogers (1986)
Valence × Social Tie	$H_{4purchase}$: The effect of positive or negative WOM on purchase intentions is accentuated when the conversation is between strong social ties rather than weak social ties.	Strong social ties influence buy/try intentions more strongly: Strong ties display more homogeneity in beliefs, attitudes, and behaviors and have high emotional intensity; thus, recommendations from strong ties should tend to motivate behavioral response.	Reingan and Kernan (1986), Brown and Reingen (1987), Gilly et al. (1998)
Valence × Channel ×Social Tie	$H_{5purchase}$: The effect of positive or negative WOM on purchase intentions is accentuated even further when it is between strong social ties in offline channels.	Strong social ties will be particularly influential in rich communication channels: User and usage imagery sources of brand value are more easily transmitted in richer communication channels, and experiential or symbolic benefits will be particularly salient in their transmission between social ties that have greater homogeneity in beliefs and attitudes.	Keller (1993)

Hypotheses for Investigation 1: Retransmission Intentions

Although theory and research has provided a relatively more substantial amount of insight into how WOM influences purchase, relatively less marketing research has focused on investigating the drivers and motivation of what makes a consumer pass along, or retransmit, a WOM message they receive from other consumers (Stephen and Lehmann 2009). The relative dearth of formal investigation into the drivers of consumption-related WOM retransmission is unexpected, given practitioners' interest in understanding how and why some brand-related content goes "viral" and much else does not (PQ Media 2009). An extensive body of literature in marketing has examined the diffusion of product adoption, but these studies focus on aggregate social structures and frequently do not investigate WOM directly. Instead, such models assume that various parameters in the diffusion model partly reflect underlying WOM activity (Mahajan et al. 1984; Mahajan et al. 1990). However, some recent marketing literature has focused on individual-level processes and retransmission (see Berger and Milkman 2010; Berger and Schwartz 2010; and Ho and Dempsey 2010). This small body of literature and more foundational psychological and sociological theories are used for the current research to develop hypotheses for how WOM valence, social tie strength, and channel of transmission may influence a WOM recipient's likelihood of retransmitting a brand-related sentiment or insight. Figure 4 depicts the research model, and Table 4 summarizes the research hypotheses.

Both negative and positive received WOM sentiment about a brand is likely to be more frequently retransmitted than neutral sentiment about a brand. For a message to be judged worthy of being retransmitted, it must first be judged to have some sort of value. Although neutral sentiment about a brand may have some worth and thus be retransmitted (e.g., because of a potentially useful objective fact about a brand), this is likely to pale in social currency when

compared with either positive or negative sentiment. Positive brand sentiment may be retransmitted for numerous reasons, such as it being helpful to others (altruism), demonstrating expertise (Higie et al. 1987), or acting as social lubrication (idle chatter; (Berger and Milkman 2010). Retransmitting negative brand information may be motivated for reasons such as helping others (serves as a warning) (Gilly et al. 1998).

> $\mathbf{H_{1retransmit}}$**:** Positive and negative WOM both have a positive influence on retransmission intentions.

Another reason positively valenced received WOM may be a stronger motivator of retransmission is that passing along positive news simultaneously serves several known motivations for why people interact with others. For example, a recent survey study of college students that sought to predict a person's self-reported frequency of online content forwarding demonstrated that altruistic motives had a positive effect on sharing frequency (Ho and Dempsey 2010). More specifically, Price et al. (1995) demonstrate that the altruistic orientation of concern for the welfare of others was a strong motivator of marketplace assistance behavior. Berger and Milkman (2010) also observe that the frequency of retransmission of *New York Times* online news articles tended to increase when the content of the news article was positive. Furthermore, Phelps et al. (2004) content-analyzed 1,259 pass-along e-mails (e.g., forwarded e-mails) consumers had received. They then examined the rate at which these e-mails were in turn forwarded again by the recipient to others. Their results suggested the messages that could be considered positive or pleasant (such as stories of good deeds) were much more likely to be passed along than were forwarded e-mails that could be characterized as negative (e.g., warnings).

All this evidence is consistent with the fundamental interpersonal relations orientation (Schutz 1958) model of why people share information with one another. More important, the retransmission of positive brand WOM simultaneously serves foundational human drives such as building social capital, altruism, and maintaining harmonious social relations (Peters and Kashima 2007). In contrast, retransmitting negative brand-related information may less consistently serve such goals because negative sentiment may be more derisive and inadvertently harm social harmony and inhibit construction of social capital.

> **$H_{2retransmit}$:** Positive WOM has a greater positive influence on retransmission intentions than negative WOM

The channel in which the WOM conversation occurred should also substantially influence the retransmission of received WOM information about a brand. No studies could be identified that explicitly compared how message retransmission likelihood differed depending on whether the initial communication occurred online or offline. However, a substantial body of marketing literature has investigated electronic communication systems precisely because of their unprecedented ability to allow people to easily reach a wide audience unbounded by geography or time (Chevalier and Mayzlin 2006; Mayzlin 2006). Marketing practitioners have also recognized this paradigm-shifting nature of such electronic communication systems: Many popular business books directly address how consumers empowered with such tools can easily and rapidly communicate in ways they never could before (Li and Bernoff 2008). Social media platforms have specific tools designed to facilitate retransmission, such as the "retweet" feature of Twitter. This body of research suggests that online channels are particularly fertile grounds for consumers to frequently retransmit received WOM messages given the relative ease. In

contrast, retransmitting messages received through offline mechanisms put a relatively greater burden on the WOM recipient. Retransmitting information received immediately requires the WOM recipient to have another proximal potential recipient or for them to immediately switch to an online channel to spread the message. Alternatively, if the offline WOM recipient wishes to retransmit the message but delay the transmission until a target becomes available, motivation to spread the message may wear off over time.

> **$H_{3retransmit}$:** WOM occurring online is more likely to be retransmitted than offline WOM.

The strength of the social tie between the WOM participants should also influence should also tend to influence message retransmission. One of the identified characteristics of communications between strong social ties is that the conversations tend to be more tailored and relevant to the participants (Granovetter 1983), and thus more valuable. Because retransmission of WOM information received about a brand is in part contingent on the perceived value of the WOM, communication between strong social ties should in turn tend to result in greater retransmission likelihood than messages between relatively weak social ties.

> **$H_{4retransmit}$:** WOM occurring between strong social ties is more likely to be retransmitted than WOM occurring between weak social ties.

A positive interaction is also likely to occur between valenced brand WOM and WOM channel. Positive and negative WOM are both expected to be perceived as more valuable social currency and thus motivate retransmission. In addition, immediate access to online channels creates immediate opportunity to retransmit WOM, and the positive effect of valenced WOM on

retransmission of a WOM message about a brand should be further accentuated when the conversation originally occurred online.

> **$H_{5retransmit}$:** The effect of both positive and negative WOM on retransmission is attenuated when WOM occurs offline.

The positive effect of valenced WOM on retransmission should also tend to be modified by the strength of the social tie between the people in the original WOM episode. Because communications between strong ties tend to be more resonant and trusted, positive and negative brand sentiment should be judged as being even more valuable by the recipient of the brand information (Chiu et al. 2007). Thus, the increased likelihood of retransmitting positive or negative WOM about a brand should be even further accentuated when the conversation occurred initially between strong social ties.

> **$H_{6retransmit}$:** The effect of both positive and negative WOM on retransmission is accentuated when the WOM occurs between strong social ties.

Figure 4: Conceptual Model: Retransmission Intentions

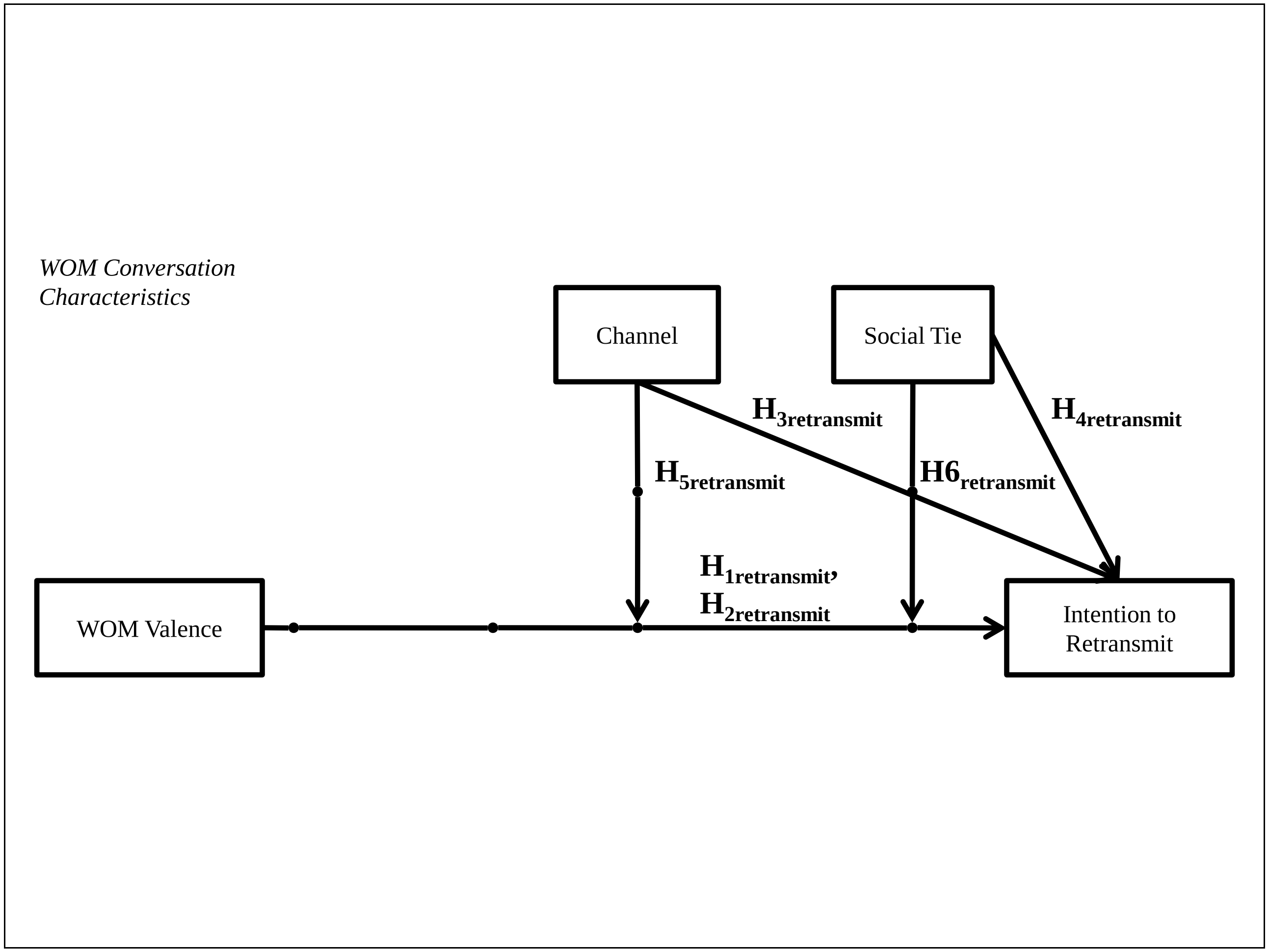


Table 4: Hypotheses Summary: Retransmission Intentions

WOM Characteristic	Hypothesis	Reasoning	Supporting Literature
Valence	$H_{1retransmit}$: Positive and negative WOM both have a positive influence on retransmission intentions. $H_{2retransmit}$: Positive WOM has a greater positive influence on retransmission intentions than negative WOM	Emotional sentiment about a brand will tend to resonate with the recipient, which will in turn be judged by the recipient to be more worthy of sharing with future audiences. The need to maintain harmonious social relations, build social capital, and share nonderisive (i.e., idle chatter) content with others will dominate as a motivation to particularly share positive brand-related content.	Berger and Milkman (2010)
Channel	$H_{3retransmit}$: WOM occurring online is more likely to be retransmitted than offline WOM.	The ease of retransmission afforded by virtue of interacting in an online context will increase retransmission likelihood of any received WOM.	Rogers (1986)
Social Tie	$H_{4retransmit}$: WOM occurring between strong social ties is more likely to be retransmitted than WOM occurring between weak social ties.	Brand-related information shared from a closely known other will tend to be more relevant and personalized, in turn increasing the likelihood that the sentiment about the brand is a candidate for retransmission.	
Valence × Channel	$H_{5retransmit}$: The effect of both positive and negative WOM on retransmission is attenuated when WOM occurs offline.	The confluence of motivation (through valenced WOM) and opportunity (through online channel) will lead to particularly greater intentions to retransmit the WOM communication.	Phelps et al. (2004)
Valence × Social Tie	$H_{6retransmit}$: The effect of both positive and negative WOM on retransmission is accentuated when the WOM occurs between strong social ties.	Affect-laden personal content will be particularly resonant and thus a candidate for retransmission when the brand sentiment comes from a well-known other (strong tie).	Chiu et al. (2007)

Hypotheses for Investigation 1: Intentions to Seek Additional Information

An extensive body of economic, psychological, and marketing literature investigates the circumstances that motivate a person to engage in various forms of external information search (for reviews applied to marketing contexts, see Brucks 1985; Huang et al. 2009; Schmidt and Spreng 1996). This research stream taps both psychological and economic theories of external search behavior to provide theoretical justification for the research hypotheses. In addition, the authors use literature on source credibility and skepticism to received information to explain how the valence, social tie strength, and channel of a brand-related WOM conversation should influence the likelihood that a WOM recipient will seek additional information about a brand. Figure 5 depicts the research model, and Table 5 summarizes the research hypotheses.

Regarding motivations for consumers to seek additional information about a brand, there are likely two key motives. First, a consumer may be skeptical or uncertain of a claim made by another about a brand and thus may be motivated to seek additional information about a brand to verify or refute the brand claim. To the extent skepticism is present about a brand claim in a WOM episode, a message receiver is more likely to want to seek information to check on the claim, presuming there is sufficient motivation and interest about the brand. Research about consumer skepticism toward advertising claims has demonstrated that consumers tend to treat subjective claims more skeptically than they do objective (fact-based) claims (Ford et al. 1990; Smith 1990). Because valenced WOM may contain more subjective opinions about a brand than neutral WOM, the skepticism perspective suggests that both positive and negative WOM will increase intentions to seek additional information than neutral WOM. It is noteworthy that consumer WOM is considered much more credible than any commercial communication (Nielsen Consumer Research 2009); thus, although skepticism about a brand-related claim from

WOM may still persist (for reasons other than a perceived commercial motive) as an explanatory mechanism motivating additional information search, it is also reasonable to suspect that the skepticism motivator may not be as salient in the context of WOM as it is when consumers consider evaluating brand-related claims made by sources with clear commercial motives.

A second factor influencing a consumer's intentions to seek additional brand information after a WOM episode is the general attraction/avoidance inspired about a brand on the basis of the sentiment of the WOM conversation. Positive sentiment about a brand is likely to create interest and attraction to a brand, motivating the respondent to seek additional information. Negative sentiment about a brand should have the opposite effect, creating avoidance of the brand, which includes less motivation to seek additional information about the brand. Thus, I hypothesize the following:

> **$H_{1seekinfo}$:** Positive WOM has a positive influence on intentions to seek additional information, and negative WOM has a negative effect.

Both motivators suggest that search will be increased when the WOM is positive about a brand. These two motivators create competing effects in the case of negative information: Skepticism of a negative sentiment motivates search but negative sentiment also creates avoidance. Because in the context of WOM (compared with previous literature examining commercial messages) the skepticism motivator may be expected to be less salient, I hypothesize that positive WOM will have a greater absolute effect on intentions to seek additional information than the absolute effect of negative WOM:

> **$H_{2seekinfo}$:** Positive WOM has a greater absolute effect on intentions to seek additional information than negative WOM.

A person's likelihood to seek additional brand information after a WOM episode is also likely to be influenced by the time and effort (search costs) required to seek additional information about the brand. Models of consumer information search, particularly those that incorporate behavioral economic approaches (Wilde 1980) to understanding external search, note the substantial negative direct relationship between search costs and extent of search (Schmidt and Spreng 1996). Similarly, researchers of electronic marketplaces have long noted that the substantially lower search costs online (Bakos 1997) than offline can drastically alter the extent of information search behavior (Lynch and Ariely 2000). Early research into electronic marketplaces in marketing have often investigated how changes to user interfaces affect search and choice (see Alba et al. 1997; Hoque and Loshe 1999; Lynch and Ariely 2000). More contemporary refinements to online search tools designed specifically for online marketplaces (Battelle 2005) and the general increase in consumer competency in using electronic marketplaces and tools (GfK Roper 2010) suggest that the cost of search online is in general much lower than offline information search. Thus, the channel of the WOM episode should in turn influence subsequent search behaviors as online WOM about brands afford recipients immediate access to low–search cost tools, whereas offline WOM conversations have a physical and temporal barrier between the WOM message content and such online tools. On the basis of this consideration, there should be greater likelihood to search information about a brand after receiving WOM about the brand through an online channel than in an offline channel:

> **$H_{3seekinfo}$:** WOM occurring offline tends to decrease intentions to seek additional information compared with online WOM.

It should be noted that this hypothesis is not contingent on an assumption that merely because a consumer engages in WOM about a brand in one channel they will not use another channel to seek additional information. In other words, in all likelihood, there are many times when a consumer receives brand information offline and later seeks more brand information online. However, this temporal and physical separation between receiving offline WOM and going to an online interface to search represents an additional cost as well, one that does not exist when the conversation initiated online in the first place.

Furthermore, it is likely that the arousal/avoidance effect of message valence on consumer information search ($H_{1seekinfo}$) will be moderated by the cost of searching out additional information about the brand. According to this idea, the positive effect of positive WOM valence will be attenuated when the conversation occurs offline when compared with an offline communication, and the negative effect of negative valence will be further exacerbated when the conversation occurs in an offline channel:

> **$H_{4seekinfo}$:** The positive effect of positive WOM on intentions to seek additional information is attenuated when the conversation occurs offline, whereas the negative effect of negative WOM on intentions to seek additional information is accentuated when the conversation occurs offline.

Moreover, investigations into the effect of source credibility have clearly shown that claims made by relatively less known others (i.e., weak ties) will tend to be met with more skepticism than if such claims were made by well-known others (i.e., strong ties). Thus, both positive and negative claims about a brand, when a well-known other makes them, should result in less skepticism on the part of the WOM receiver and therefore generate less desire to seek additional information about the brand in question. Inversely, when positive or negative information is shared by a relatively unknown social tie, the skepticism about the claim should

be greater and, thus, there should be more motivation to seek additional brand information. In addition, it has been noted that there is a general difference in the fluency strong ties tend to exhibit between one another during communication than when conversations occur between weak ties. Bernstein's (1964) notions of restricted communication (many meanings tend to be implicit or taken for granted between familiar actors) and elaborated communication (codes are more complex but universal as greater effort is required to ensure understanding is reached) have been observed to correspond heavily with the type of social tie between actors (Coser 1975). Because strong ties tend to communicate using restricted communication, the presumption of mutual understanding and fluency between the communicators implies that a recipient of brand information will be less inclined to need to verify the content. Conversely, the elaborated communication tendency between weak ties suggests that there is more opportunity for incomplete understanding when a consumer receives brand-related sentiment. These systematic differences in social tie communication styles further suggest that how the brand-related valence in a WOM conversation affects intentions to seek additional information will be moderated by the social tie strength. This interaction between the valence of the WOM and the relationship between the social actors is as follows:

> **$H_{5seekinfo}$:** The positive effect of positive WOM on intentions to seek additional information is attenuated when the conversation occurs between strong social ties, whereas the negative effect of negative WOM on intentions to seek additional information is accentuated when the conversation occurs between strong social ties.

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Figure 5: Conceptual Model: Seek Additional Information Intentions

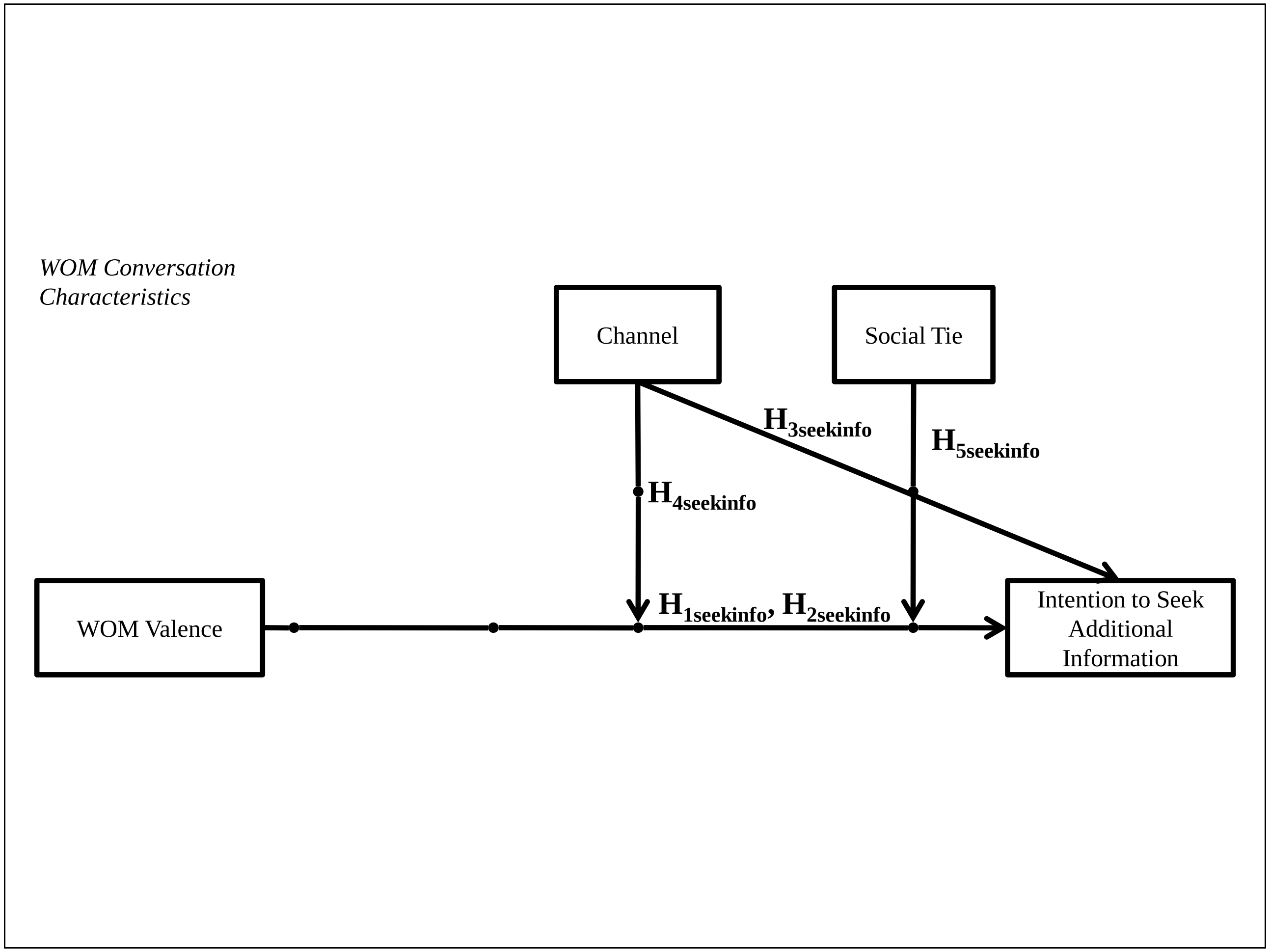


Table 5: Hypotheses Summary: Seek Additional Information Intentions

WOM Characteristic	Hypothesis	Reasoning	Supporting Literature
Valence	$H_{1seekinfo}$: Positive WOM has a positive influence on intentions to seek additional information, and negative WOM has a negative effect. $H_{2seekinfo}$: Positive WOM has a greater absolute effect on intentions to seek additional information than negative WOM.	In general, arousal/avoidance tendencies toward a brand will tend to dominate the skepticism effect about information shared about a brand in terms of motivating WOM recipients to seek additional brand info. However, because both positive information creating arousal and skepticism both motivate increased brand search, the absolute effect of positive information should be greater than negative brand WOM.	Smith (1990), Ford et al. (1990)
Channel	$H_{3seekinfo}$: WOM occurring offline tends to decrease intentions to seek additional information compared with online WOM.	Lower search costs associated with online channels should inherently lead to more brand-related search when any sort of WOM about a brand is received in an online channel because access to online search tools are immediately at the WOM receiver's fingertips.	Lynch and Ariely (2000), Schmidt and Spreng (1996)
Valence $\times$ *Channel*	$H_{4seekinfo}$: The positive effect of positive WOM on intentions to seek additional information is attenuated when the conversation occurs offline, whereas the negative effect of negative WOM on intentions to seek additional information is accentuated when the conversation occurs offline.	The positive arousal effect of positive WOM on information search will not be as substantial when the WOM occurs in channels that reduce the immediate ability and opportunity to investigate the claim. Likewise, the negative avoidance effect of negative WOM will be even further exacerbated when the search cost associated with investigating the brand is relatively higher.	
Valence $\times$ *SocialTie*	$H_{5seekinfo}$: The positive effect of positive WOM on intentions to seek additional information is attenuated when the conversation occurs between strong social ties, whereas the negative effect of negative WOM on intentions to seek additional information is accentuated when the conversation occurs between strong social ties.	Subjective brand sentiments will not be met with as much skepticism when the WOM comes from a relatively well-known and trusted source. There will be less motivation to seek additional information about the brand because the brand sentiment will tend to be accepted at face value.	

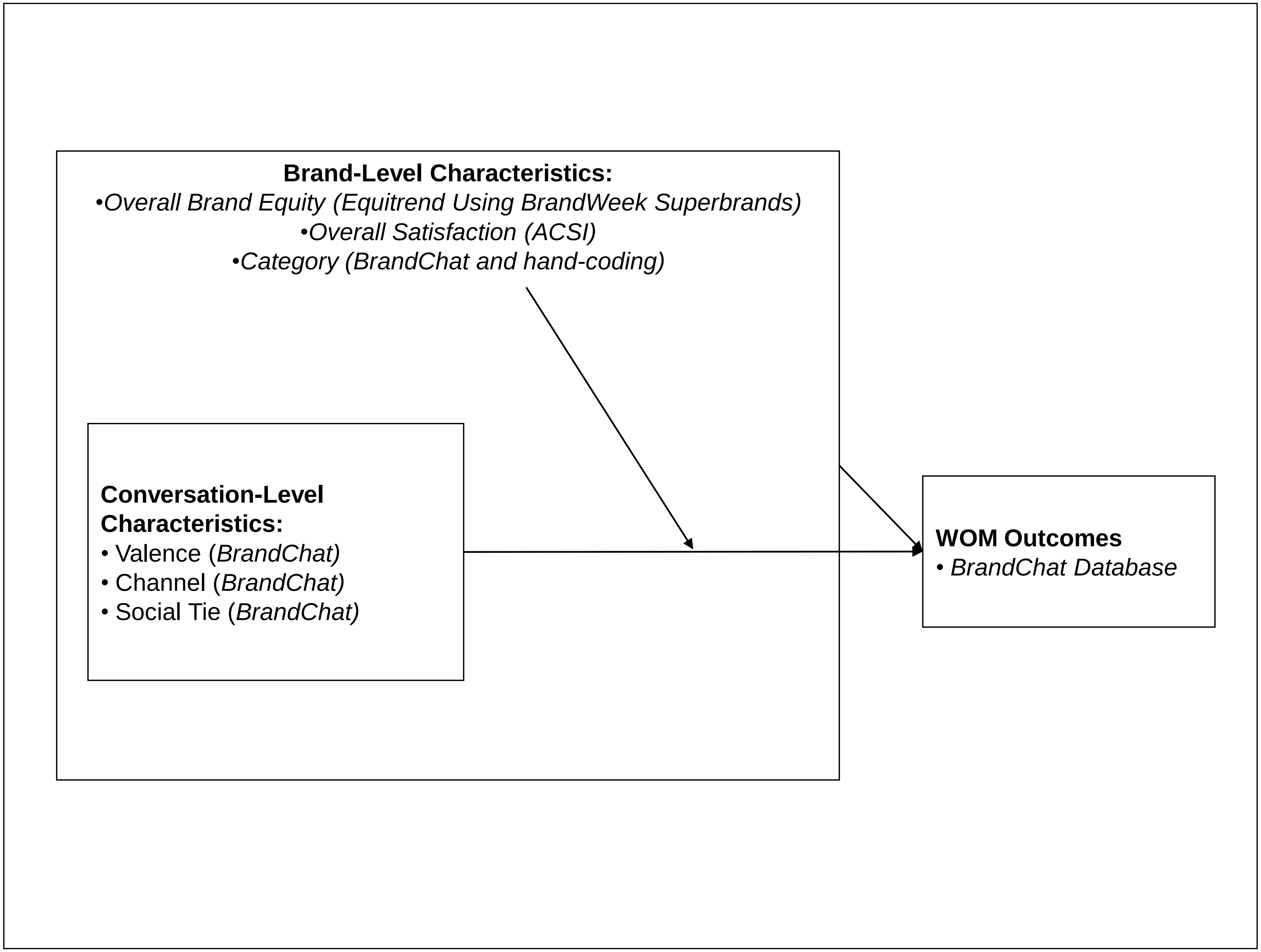
DATA AND METHOD FOR INVESTIGATION 1

Next, I explain the research design and methodology used to test the conceptual model and research hypotheses. I begin with a discussion of details of each database and the variables used, because the proposed method to test the hypotheses requires the integration and analysis of several private and publicly available marketing databases. Potential limitations and challenges of using and linking the databases are considered as well, and I note how I addressed these concerns. Then, I briefly discuss considerations for the statistical techniques necessary to test the hypotheses as well.

To test the research hypotheses and conceptual model, data requirements are significant. First, particularly rich brand-level WOM data are required, with depth beyond the mere valence of the conversation and volume of the WOM. . For example, it is necessary to know the relationship structure of the participants in the WOM episode (e.g., strong vs. weak ties). Second, both offline and online brand-level WOM is necessary. Third, it is necessary to have individual-level responses to detect how a WOM recipient responds as a consequence of the WOM episode. Furthermore, to at least partially test the complete conceptual model, information about brand-level marketing actions (e.g., information about brand-specific characteristics such as media spend, overall brand strength, and primary product category) are required to complement WOM conversation data. Next, I discuss the characteristics of the BrandChat[1] Database, TNS Ad$pender, ACSI, and Equitrend's Brand Equity data to explain how these secondary sources meet the data requirements necessary to test the conceptual model and hypotheses. Figure 6 summarizes how the discussed secondary databases provide the variables necessary to test the conceptual model and hypotheses.

[1] I use the term "BrandChat" to keep the proprietary database anonymous.

Figure 6: Proposed Data Sources for Model Variables



Databases Used for Analysis

BrandChat Database

The BrandChat Database is a proprietary database developed and maintained by a marketing consulting firm specializing in providing clients with highly detailed longitudinal information about U.S. consumers' WOM activity both offline and online. To our best knowledge, this unique database has not been used in any published academic research. Every month since 2006, an average of slightly more than 700 respondents are recruited to participate in the panel. The respondents are selected to be demographically-representative of the United States for people from 13 to 69 years of age. Table 6 illustrates the general demographic composition of a monthly BrandChat panel for the years 2007, 2008, and 2009 and compares it with U.S. census data. Comparing the demographic composition of the BrandChat database to available U.S. census data suggests that the BrandChat is representative of the population, though BrandChat participants may tend to have slightly lower overall levels of graduate education, fewer respondents that would have identified as "Other" in the BrandChat database, fewer respondents with high (>$100,000) household incomes (though many BrandChat participants did not or refused to respond to this question), a greater concentration of younger consumers (13–29 years), and fewer older respondents (60–69 years). These differences may be partly attributable to random error, differences in the wording and presentation of demographic questions asked in BrandChat versus Census surveys, differences in the time frame analyzed (e.g., BrandChat 2008 versus the 2000 U.S. Census), or systematic differences in the survey pool of potential BrandChat respondents that persists despite efforts to create a perfectly demographically representative sample.

Table 6: Average Demographic Characteristics of BrandChat Weekly Panel Respondents, by Year

	BrandChat 2007		BrandChat 2008		BrandChat 2009		U.S. Census
Education	Avg./Week	%	Avg./Week	%	Avg./Week	%	
Grade school or less	28.2	3.9%	25.6	3.5%	24.9	3.4%	5.0%
Some high school	129.7	18.1%	128.7	17.7%	130	17.9%	9.1%
High school graduate	203.3	28.4%	199.3	27.4%	198.5	27.3%	30.9%
Trade school/technical school	28.3	4.0%	30.7	4.2%	26.2	3.6%	3.9%
Associates degree/junior college	37.4	5.2%	36.4	5.0%	40.8	5.6%	4.6%
Some college	119.7	16.7%	113.9	15.7%	113.9	15.7%	19.5%
College graduate	113.8	15.9%	107.9	14.9%	111.6	15.4%	17.7%
Post graduate or more	55.4	7.7%	57.6	7.9%	53.6	7.4%	9.3%
Race							
Caucasian/white	561.4	78.4%	547.2	75.3%	547.3	75.3%	74.5%
African-American	85.6	12.0%	84.1	11.6%	83.8	11.5%	12.4%
Asian	30.2	4.2%	29.6	4.1%	29.5	4.1%	4.4%
Other	0		15	2.1%	17.4	2.4%	8.8%
Refused	21.5	3.0%	21	2.9%	20.9	2.9%	N/A
Income							
< $75k	458	64.0%	456.1	62.8%	472.4	65.0%	69.5%
$75k +	138.1	19.3%	141.5	19.5%	141.8	19.5%	30.4%
$100k +	69	9.6%	70.7	9.7%	70.6	9.7%	19.6%
Don't Know/Refused	120.1	16.8%	102.7	14.1%	86.1	11.9%	N/A
Age Groups							
13–19 years	106.5	14.9%	105.9	14.6%	105.8	14.6%	10.3%
20–29 years	116.2	16.2%	110.2	15.2%	107.9	14.9%	19.6%
30–39 years	152.9	21.4%	147.9	20.4%	144.6	19.9%	22.1%
40–49 years	141.6	19.8%	142.1	19.6%	146.9	20.2%	21.7%
50–59 years	136.9	19.1%	131.2	18.1%	130.4	17.9%	15.9%
60–69 years	61.7	8.6%	62.8	8.6%	64.6	8.9%	10.4%
Gender							
Men	351.9	49.2%	343.8	47.3%	342.6	47.2%	49.1%
Women	364.2	50.9%	356.2	49.0%	357.4	49.2%	50.9%
Totals	715.9	100.0%	726.50	100.0%	726.5	100.0%	100%

Values may not sum to totals because of rounding errors or nonresponse. Education attainment comes from U.S. Census Bureau, Current Population Survey, 2009 Annual Social and Economic Supplement, 18 years an older. Race comes from U.S. Census Bureau 2005–2009 American Community Survey & included Native Hawaiian and Pacific Islander (coded here as Other), Two or more races (coded here as Other), and American Indian and Alaska Native (coded here as Other). Income comes from the 2009 U.S. Census Bureau Annual Social and Economic Supplement. Age and Gender comes from U.S. Census Bureau, Census 2000 Summary File 1, Matrices P13 and PCT12. Age group "13–1 9 years" reported here is actually "15–19 years" for census data.

Panel respondents are asked to take notes on product and brand conversations they have during a 24-hour period. Face-to-face, on the phone, and various online communication channels are all potential channels in which product and brand conversations can occur. The respondent uses a dairy-like survey instrument to aid in documenting details about product and brand-related conversations. Respondents are asked to recall the basic frequency and product category of all product and brand conversations.[2] However, to avoid respondent fatigue, a random selection (but no more than 10 conversations per respondent) of those conversations are selected to have the respondent elaborate about the content and context of the conversation.

Figure 7 depicts the basic structure of information captured in the BrandChat database about the respondent, the conversation, other participants in the conversation, brand-specific information in the conversation, and respondent outcomes due to the conversation. For each respondent, BrandChat collects demographic information and media consumption habits. In addition, product category involvement variables are captured by having the respondent identify any product categories he or she (1) follows closely or (2) gives advice about. The respondent's social network size is assessed as well, measured by the respondent's report of their number of friends, number of family members, number of acquaintances, and involvement in community organizations.

The respondent also reports additional details about the product and brand conversations. The number of people involved in the conversation is measured (mode = 2), the channel the conversation occurred (e.g., in person, over the telephone, through social media) as well as

[2] BrandChat categories include Automotive, Financial, Health/Healthcare, Food/Dining, Beverages, Technology, Telecommunications, Travel Services, Personal Care/Beauty, Household Products, The Home, Children, Retail/Apparel, Media/Entertainment, Sports/Recreation/Hobbies, and Non-Profit/Charity/Advocacy Groups

where the conversation occurred (e.g., at home, at work). Brands mentioned in the conversation and the overall valence of the conversation about the brand(s) (mostly positive, mostly negative, neutral, or mixed) is also captured in the BrandChat database. If specific advice was provided about a product or brand, the respondent documents which participant in the conversation gave the advice (or whether both did) as well as whether the advice was based on personal experience. If brand advice was given to the respondent, additional details about the advice provider are captured using the BrandChat participant's recollection. The gender, age, and relationship of the advice provider to the BrandChat panel respondent are measured, and the credibility/believability of the advice is measured and the specific type of advice (buy it, try it, consider it, or avoid it). In addition, possible consequences of the provided advice is measured: The respondent reports his or her propensity to purchase the product/brand, relay the WOM communication to other people, and seek additional information about the product/brand.

A limitation of the BrandChat WOM database is that the user interface used to generate reports—and the only mechanism I could use to extract data—is highly tailored to serve a managerial audience, not necessarily a research audience. A consequence of this system is that not all WOM characteristics available in BrandChat can be simultaneously extracted at once. The impact of this limitation for this dissertation is that only WOM characteristics relevant to the hypotheses could be extracted, and other characteristics that may have had some additional relevance could not be used. For example, although the BrandChat database tracks the physical location in which a WOM conversation occurs, the data could not be extracted from the system while also extracting all the WOM characteristics relevant to the research hypotheses. The implications of this limitation are discussed at the end of Investigation 1.

WOM Valence

The valence of the WOM conversations about a brand is reported as positive, negative, neutral, or mixed for a specific brand. (A WOM episode may be positive for one mentioned brand, but negative for another.) Participants in the BrandChat panel are asked to reflect whether the general tenor of the conversation about the brand was one of the four possible valence answers. I used dummy codes to operationalize the WOM valence, because this approach (rather than presuming an underlying valence continuum) enabled me to estimate differential effects between neutral and mixed sentiment as well as capture different absolute effects from positive or negative WOM.

WOM Channel

The channel of the WOM episode is coded as either offline (face-to-face or telephone) or online (e.g., e-mail, text message, blog, Twitter). The BrandChat respondent was asked to recall in which of these available channels the conversation occurred. The decision to include telephone conversations as offline (and thus designated by the theorization supporting the hypotheses as rich media) was based on the consideration that aside from lacking the ability to see nonverbal communications of face-to-face conversations, telephone conversations carried all of the other signals linked with rich channels of communication (e.g., synchronousness, the transmission of subtle tonal inflections in conversation, interactivity with immediate feedback). Literature on media richness supports the designation of telephone conversations as a particularly rich form of communication (Daft and Lengel 1986; Dennis and Kinney 1999; Rogers 1986).

Social Tie Strength

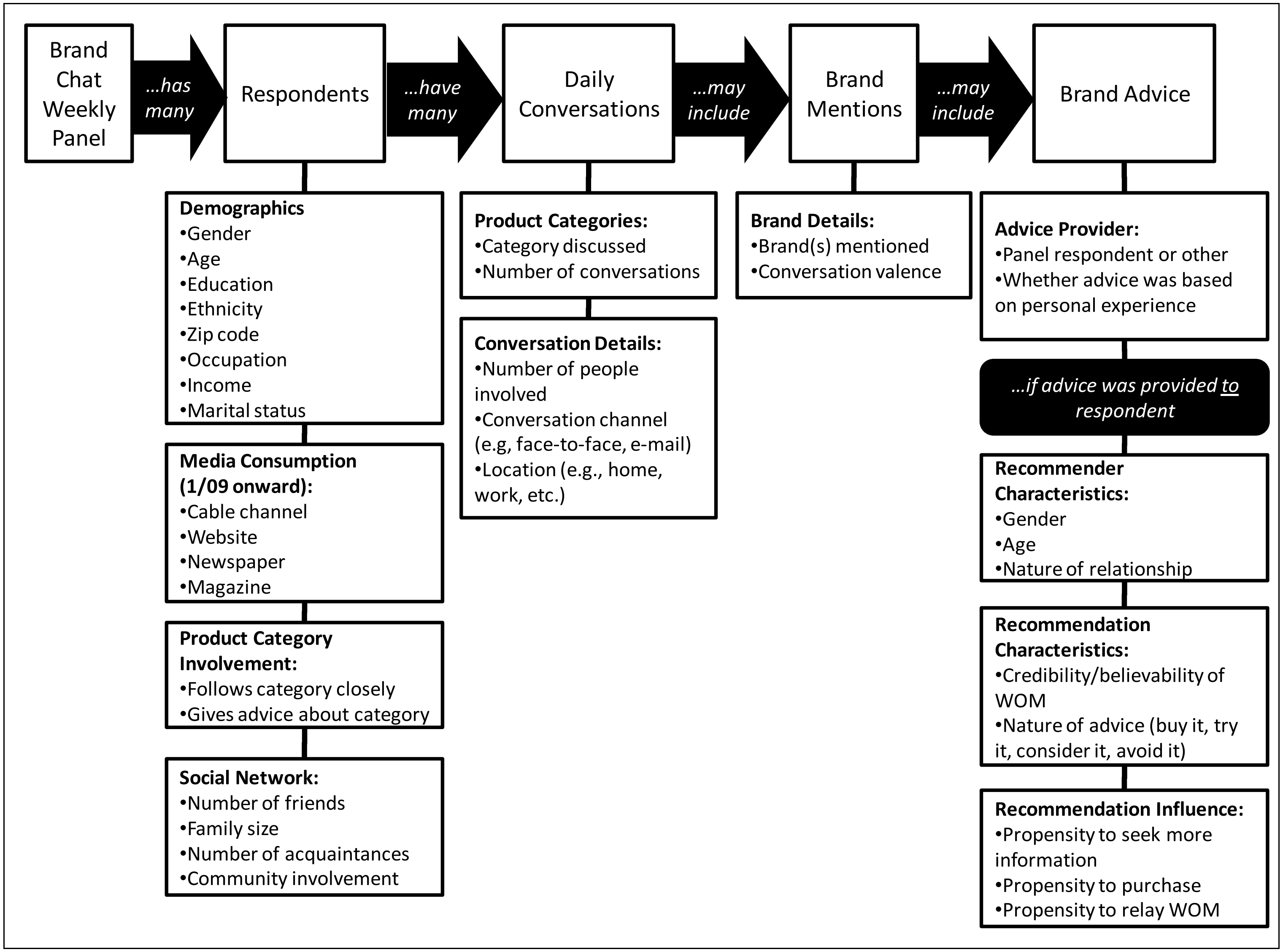
Tie strength in the WOM dyad is coded as weak tie, strong tie, or professional/expert. BrandChat participants identify their relationship with the person in the WOM episode as spouse/partner, family member, best friend, personal friend (coded as strong tie), coworker, other acquaintance, stranger (coded as weak tie), or a professional/expert on the topic. Tie strength is often conceptualized as a continuous, latent construct, though some researchers have considered it a multidimensional construct (Marsden and Campbell 1984). Thus, it would be ideal to have a continuous measure of tie strength rather than code using social relationships. However, De Bruyn and Lilien (2008) conduct a study in which Frenzen and Davis's (1990) tie strength scale was completed along with nearly the same relationship designations as those in BrandChat. The mean social tie value of "another relative" in their data set (the lowest scored tie among those that are identified as strong ties in this dissertation) was significantly higher/stronger ($p < .001$) than the mean value of "coworker" (the highest scored tie among those identified as weak ties in this dissertation). In addition, a review of literature about social tie strength measurement indicates that a person self-identifying his or her social relationship with another is a reasonable way to distinguish between weak and strong ties (Marsden and Campbell 1984). This provides evidence that using social relationship indicators for tie strength is consistent with the tie strength construct.

Dependent Variables: Intentions to Purchase, Retransmit and Seek Additional Information

Consequences of the brand-related WOM conversations is measured using the BrandChat panel participants' self-report of their propensity to (1) purchase the product/brand, (2) relay the WOM communication to other people, and (3) seek additional information about the

product/brand. Each of these questions are measured on a 0 (“not at all likely”) to 10 (“extremely likely”) scale. BrandChat respondents were asked to respond with a score of 10 if they had already taken the indicated action in the previous 24 hours. A limitation of this measure is that it is impossible to distinguish those respondents who have strong intentions to take the action and those who have already taken the behavior. However, given that participants are reflecting only on the past 24 hours of WOM activity, it is reasonable to suppose that in most cases there simply has not been an opportunity to act. Thus, a score of 10 should be considered a strong intention to act and not necessarily evidence of the behavior already occurring. An advantage of this measure is that it provides a direct assessment of the actual WOM participant’s perception of the impact of a conversation.

Figure 7: Overview of BrandChat Database



Analyzed Sample

654 brands (level 2) were selected for analysis from the BrandChat database with a total of 188,510 conversations (level 1). Only a subset of the WOM conversations captured by the BrandChat database were retained as candidates for analysis for this study. Specifically, although BrandChat captures basic information about all WOM conversations a respondent had in the previous 24 hours, a BrandChat respondent would only evaluate their intention to buy a particular brand discussed if the following conditions were true: (1) Another person in the WOM episode gave specific advice about the brand, and (2) that particular brand was one of the up to 10 brands randomly selected (if the respondent identified more than 10 brands) by the BrandChat guided questionnaire to receive thorough follow-up questions after the respondents initially mentioned the brands. The current analysis includes WOM conversations that occurred between July 2006 and March 2010.

Several criteria were used to select brands for inclusion in the model. First, the BrandChat guided survey included some categories that allowed for respondents to provide information for topics that did not qualify as brands for the present analysis. For example, political figures and famous personalities populated the BrandChat database but were not included in the analysis. BrandChat responses that were about general product categories rather than specific brands were also not included. Moreover, brands that were likely to be represented in the BrandChat database for only a short period of time were not included for analysis. For this reason, media properties (e.g., television shows, movies, video games) were not included in the analysis. In addition, in some cases, it was ambiguous what brand was being referenced (e.g., brands that may have been misspelled, brands using generic words without any contextual information provided to identify the specific brand); these brands were also excluded from

analysis. Brands were retained as candidates for analysis in cases in which brand misspellings or ambiguous brands could be corrected because of evidence provided through other contextual information provided in BrandChat responses. Finally, some brands in the BrandChat database were not included because they did not include any WOM episodes in which the BrandChat respondent was given a brand recommendation. This initial pruning reduced the 1,514 unique brands/topics in the BrandChat database to 938 brands.

In addition, given the hierarchical structure of the data (a consumer's intentions to purchase, retransmit, or seek additional information based on a WOM recommendation clustered around brands), brands were only included for analysis if there were at least 30 WOM recommendations made about the brand. This is aligned with the recommendation that a suitable number of cases populate the level-1 model of a hierarchical model to derive more accurate estimates and standard errors in the fixed portion of the model, also known as the 30/30 rule (i.e., at least 30 groups, each with at least 30 cases) (Kreft 1998). This criterion resulted in 654 brands retained for the analysis. Additional details and rationale for how the reactions to WOM were clustered within brands is addressed in further detail in the analysis section of this dissertation.

On average, a brand had 288.2 conversations; the maximum number was 6,619 conversations (Coca-Cola). The first quartile was denoted by 62 conversations and the third quartile by 253 conversations. The distribution of WOM conversations across brands in the analyzed sample is similar to the observation made by Niederhoffer et al. (2007), who observed that 85% of the WOM conversations about consumer packaged goods came from 10% of the brands. In this case, 15.1% of the brands (10.9% had the 30/30 rule not been applied) represented 85% of all WOM conversations. Figure 8 depicts the frequency of WOM conversations by brand sorted by frequency. Select brand names are included for illustrative

purposes. Table 7 summarizes the aggregate descriptive statistics for the intention to purchase, retransmit, and seek additional information, and Table 8 is a cross tabulation of WOM conversations across the three focal WOM properties (valence, social tie, and channel). As expected, a much greater percentage of brand conversations occur between strong social ties (79.14%) than weak social ties (18.56%). In general, the valence of all conversations was positive (61.37%), and negative brand sentiment (8.63%) trailed behind neutral (12.62%) and mixed (17.38%) WOM about the brand. The majority of brand conversations were offline (94.75%).

Figure 8: Frequency of WOM Conversations by Brand

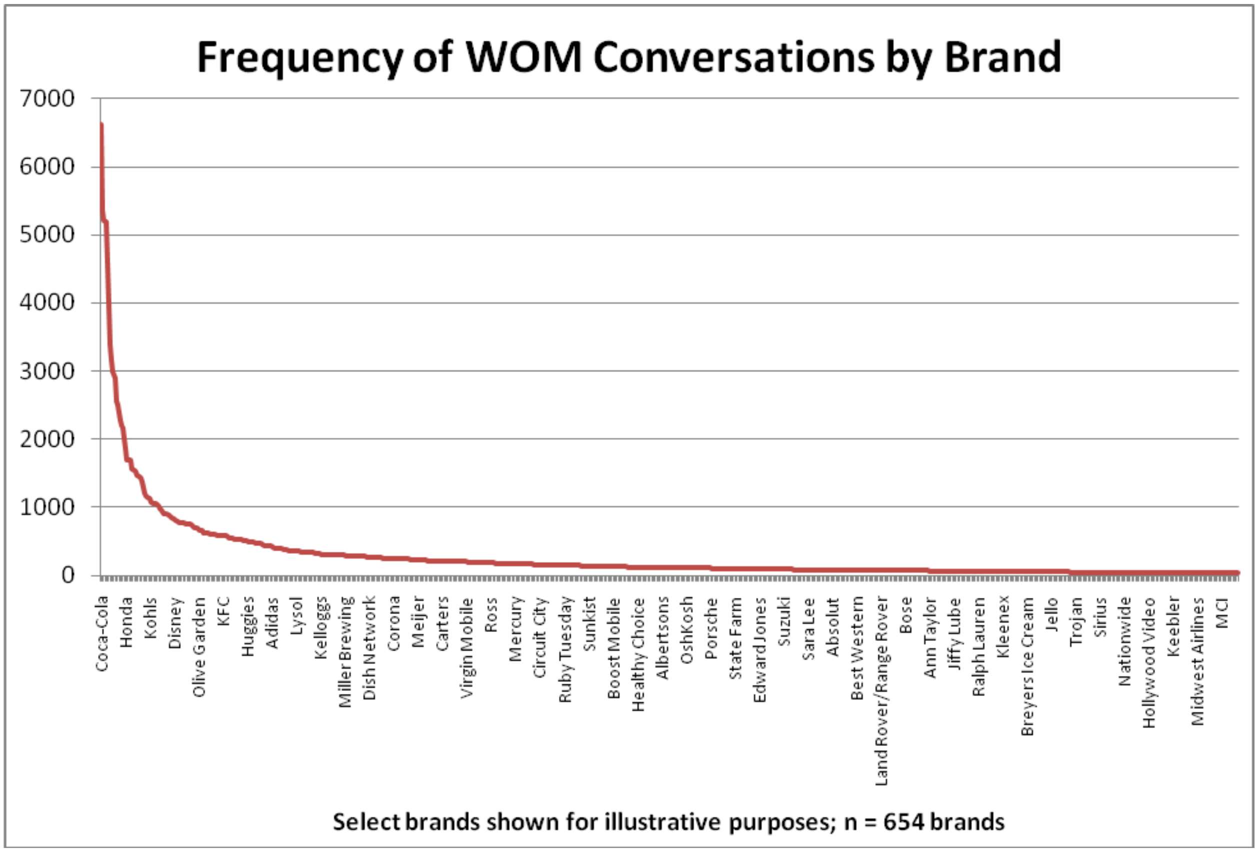


Table 7: Descriptive Statistics of Analyzed Sample

	M	SD.	Variance	Skewness	Kurtosis
Purchase	7.43	2.18	4.75	–1.39	4.71
Resend	7.47	1.67	2.78	–1.52	6.88
Seek	6.04	2.00	4.01	–0.74	3.96

n=188,510.

Table 8: Tabulation of WOM Count by Valence, Channel, and Social Tie

		Valence				
		Positive	**Negative**	**Neutral**	**Mixed**	**Total**
Social Tie	**Channel**					
Strong	**Offline**	89,173 (47.3%)	11,375 (6.03%)	17,860 (9.47%)	23,223 (12.32%)	141,631 (75.13%)
	Online	4,436 (2.35%)	828 (0.44%)	826 (0.44%)	1,470 (0.78%)	7,560 (4.01%)
Weak	**Offline**	18,671 (9.9%)	3,410 (1.81%)	4,109 (2.18%)	6,832 (3.62%)	33,022 (17.52%)
	Online	1,018 (0.54%)	216 (0.11%)	274 (0.15%)	457 (0.24%)	1,965 (1.04%)
Expert	**Offline**	2,190 (1.16%)	404 (0.21%)	659 (0.35%)	697 (0.37%)	3,950 (2.1%)
	Online	197 (0.1%)	42 (0.02%)	67 (0.04%)	76 (0.04%)	382 (0.2%)
	Total	115,685 (61.37%)	16,275 (8.63%)	23,795 (12.62%)	32,755 (17.38%)	188,510 (100%)

Percentages reported in parentheses.

ANALYSES AND RESULTS FOR INVESTIGATION 1

The initially proposed structure of the random coefficient regression model used to assess the hypotheses for the three dependent variables is depicted in Equation 1. The model shown is for purchase intentions ($BUY_{c,b}$), but it the same for the other two dependent variables ($TRANSMIT_{c,b}$ and $SEEKINFO_{c,b}$). The subscript *c* denotes conversation, which is the first-level portion of model. The subscript *b* denotes brand, which is the second level of the model. All other conventions for the subscripts are consistent with recommendations from popular multilevel modeling literature (Cohen et al. 2003; Enders and Tofighi 2007). This initial model proposes all two- and three-way interactions for all independent variables relevant to the research hypotheses.

Table 9 provides a description of how each variable listed in the random coefficient regression is coded and how it corresponds to the BrandChat database. The next section considers alternative specifications of the model and investigates model assumptions. Then, the results of the hypotheses and discussion of the results is presented for each dependent variable.

Equation 1: Random Coefficient Regression Model: Purchase Intentions

$$
\begin{aligned}
BUY_{c,b} = {} & (\gamma_{0,0} + u_{0,b}) + \\
& (\gamma_{1,0} + u_{1,b}) * ValPos_{c,b} + (\gamma_{2,0} + u_{2,b}) * ValNeg_{c,b} + (\gamma_{3,0} + u_{3,b}) * ValMix_{c,b} + \\
& (\gamma_{4,0} + u_{4,b}) * ChnOffl_{c,b} + (\gamma_{5,0} + u_{5,b}) * SocTS_{c,b} + (\gamma_{6,0} + u_{6,b}) * SocTE_{c,b} + \\
& (\gamma_{7,0}) * ValPos_{c,b} * ChnOffl_{c,b} + (\gamma_{8,0}) * ValNeg_{c,b} * ChnOffl_{c,b} + (\gamma_{9,0}) * ValMix_{c,b} * ChnOffl_{c,b} + \\
& (\gamma_{10,0}) * ValPos_{c,b} * SocTS_{c,b} + (\gamma_{11,0}) * ValNeg_{c,b} * SocTS_{c,b} + (\gamma_{12,0}) * ValMix_{c,b} * SocTS_{c,b} + \\
& (\gamma_{13,0}) * ValPos_{c,b} * SocTE_{c,b} + (\gamma_{14,0}) * ValNeg_{c,b} * SocTE_{c,b} + (\gamma_{15,0}) * ValMix_{c,b} * SocTE_{c,b} + \\
& (\gamma_{16,0}) * SocTS_{c,b} * ChnOffl_{c,b} + (\gamma_{17,0}) * SocTE_{c,b} * ChnOffl_{c,b} + \\
& (\gamma_{18,0}) * ValPos_{c,b} * ChnOffl_{c,b} * SocTS_{c,b} + (\gamma_{19,0}) * ValNeg_{c,b} * ChnOffl_{c,b} * SocTS_{c,b} + (\gamma_{20,0}) * ValMix_{c,b} * ChnOffl_{c,b} * SocTS_{c,b} + \\
& (\gamma_{21,0}) * ValPos_{c,b} * ChnOffl_{c,b} * SocTE_{c,b} + (\gamma_{22,0}) * ValNeg_{c,b} * ChnOffl_{c,b} * SocTE_{c,b} + (\gamma_{23,0}) * ValMix_{c,b} * ChnOffl_{c,b} * SocTE_{c,b} + \\
& \sum_{i=2}^{15} (\gamma_{22+i,0}) * Qi_{c,b} + (\gamma_{0,1}) * BrVol_b + (\gamma_{1,1}) * BrVol_b * ValPos_{c,b} + (\gamma_{2,1}) * BrVol_b * ValNeg_{c,b} + (\gamma_{3,1}) * BrVol_b * ValMix_{c,b} + \\
& (\gamma_{0,2}) * BrPosPct_b + (\gamma_{1,2}) * BrPosPct_b * ValPos_{c,b} + (\gamma_{2,2}) * BrPosPct_b * ValNeg_{c,b} + (\gamma_{3,2}) * BrPosPct_b * ValMix_{c,b} + r_{c,b}
\end{aligned}
$$

Table 9: Description of Variables Used in Analysis

Variable Name	Description
$BUY_{c,b}$	BrandChat respondent's answer to the question "How likely is it that you will purchase the brand or buy something from that company?" (0 = Not at All Likely, 10 = Extremely Likely)
$TRANSMIT_{c,b}$	BrandChat respondent's answer to the question "How likely is it that you will pass along to others what you have learned from other people in the conversation?" (0 = Not at All Likely, 10 = Extremely Likely)
$SEEKINFO_{c,b}$	BrandChat respondent's answer to the question "how likely is it that you will seek additional information about the brand or company, based on what you heard from other people in that conversation" *(0 = Not at All Likely, 10 = Extremely Likely)*
$ValPos_{c,b}$	Centered within brand recoded dummy variable indicating if the BrandChat respondent characterized the conversation about the brand as "mostly positive"
$ValNeg_{c,b}$	Centered within brand recoded dummy variable indicating if the BrandChat respondent characterized the conversation about the brand as "mostly negative"
$ValMix_{c,b}$	Centered within brand recoded dummy variable indicating if the BrandChat respondent characterized the conversation about the brand as "mixed"
$ChnOffl_{c,b}$	Centered within brand recoded dummy variable indicating if the BrandChat respondent said the conversation occurred via (1) "face to face" or (2) "on the phone" ** Conversation was coded online if respondent indicated conversation occurred through: (1) "email", (2) "instant/text message", or (3) "through an online chatroom, blog, Twitter, or social networking site"*
$SocTS_{c,b}$	Centered within brand recoded dummy variable indicating if the BrandChat respondent said the conversation was with a strong social tie, identified in the BrandChat system as (1) "spouse/partner", (2) "family member", (3) "best friend", or (4) "personal friend".
$SocTE_{c,b}$	Centered within brand recoded dummy variable indicating if the BrandChat respondent said the conversation was with an expert, identified in the BrandChat system as a "professional or expert on the topic". **Conversation was coded as being between a weak social tie if BrandChat respondent said the conversations was with a (1) "co-worker", (2) "other acquaintance", or (3) "stranger".*
$Q2_{c,b}$ — $Q15_{c,b}$	Dummy variables indicating the quarter the conversation took place (Q15 = Jan.-March 2010).
$BrVol_b$	Mean-centered sum of all WOM conversations for a particular brand.
$BrPosPct_b$	Mean-centered percentage of all WOM conversations for a particular brand that were characterized as being "mostly positive."

In this model, all coefficients denoted by $\gamma_{c,0}$ represent population regression coefficients for the respective level 1 (WOM conversation) predictors. The population regression intercept, $\gamma_{0,0}$, is partnered with $u_{0,b}$, which indicates that the intercept for a particular brand is allowed to vary. Likewise, the coefficients representing the main effects of WOM valence ($\gamma_{1,0}$; $\gamma_{2,0}$; and $\gamma_{3,0}$) are paired with variables ($u_{1,b}$; $u_{2,b}$; and $u_{3,b}$) that indicate that the main effects of WOM conversation valence for a particular brand is allowed to vary. The main effects for WOM channel and social tie strength are also allowed to randomly deviate across brands on their respective population regression coefficients.

In addition, a series of covariates were introduced into the model: (1) dummy variables indicating the quarter the WOM conversation happened, (2) the volume of WOM observed for a given brand (mean-centered level 2 variable, x-bar = 288.6,σ = 604.3) and its interaction with WOM valence, and (3) the percentage of all WOM for a brand that was positive (mean-centered level 2 variable, x-bar = .41,σ = .34) and its interaction with WOM valence. The time covariates were introduced to control for any dramatic shifts in WOM impact across time (e.g., if WOM had greater impact during the holiday season by virtue of more people actively shopping for a wider array of products for a wider array of people). The time covariates did not exhibit any pattern of results that were a priori speculated to potentially emerge. The WOM volume covariates were introduced to control for the influence of a given WOM episode being confounded with a buildup of prior WOM conversations. Although the BrandChat questionnaire specifically prompts the respondent to answer about their purchase, retransmission, and information search intentions as a result solely of the immediate conversation, this covariate was introduced to control for a respondent's WOM impact based on a brand's popularity to be

discussed among consumers. The inclusion of the covariate of a brand's percentage of positive WOM is used to control for the impact of a particular WOM episode being incorrectly attributed to the overall favorableness/unfavorableness of brand WOM sentiment. Investigation 2 explores more formally how brand-level characteristics influence the impact of a given WOM episode.

Neutral WOM was used as the reference category for the WOM valence dummy variables because it provides a natural reference point from which to compare the relative effect sizes of positive and negative WOM. Online WOM was selected as the reference variable among the WOM channel dummy variables. Weak social ties were the reference category among the three social tie variables. This reference variable was selected because it allows for easier comparison of how strong social ties affect intent to purchase compared with weak social ties; alternatively, using experts as the reference variable for social tie would lend to more awkward interpretations unrelated to the current research hypotheses (i.e., comparing the effect of strong and weak social ties with experts was not a focal component of the analysis).

The data and model were analyzed using STATA IC version 11.0 software. The XTMIXED procedure was used because it is designed to facilitate multilevel mixed-effects linear regression. Residuals were assumed to be i.i.d. Gaussian with the same variance. Models with random slopes were allowed to have distinct variances and covariances for all random effects. Models were estimated using restricted maximum likelihood. For all models presented, at least 100 expectation-maximization iterations were performed, and all models reached convergence.

All within-level variables (characteristics of the WOM characteristics) relevant to the research hypotheses (valence, channel, and social tie) investigated in this study were centered

within cluster (CWC). In other words, all dummy codes were recoded to reflect mean-centering within a particular brand. This option was chosen instead of centering on the grand mean (CGM) because of the difficulty of interpreting level 1 coefficients when using CGM, because it does not remove the between-level variance from a variable. In a review of the pros and cons of CWC and CGM, Enders and Tofighi (2007, p. 127) state that because CGM clustering result in scores containing both level 1 and level 2 variation, regression slopes become an "ambiguous mixture of Level 1 and Level 2 association between X and Y." In contrast, CWC, results in an estimate that provides an unbiased level 1 estimate. Because this substantive interest in this present analysis is focused on level 1 variables (e.g., properties of the WOM conversation), Enders and Tofighi (2007) recommend CWC. It is also noteworthy that Raudenbush and Bryk (2002) note that group mean-centering provides a more accurate estimate of slope variance and covariance (e.g., heterogeneity of regression betas between brands). This is also of additional interest for the main effects because understanding the degree of variation of different types of WOM valence on purchase intentions across brands can signal the extent to which the main effect depends on a particular brand. One consequence of this approach is that the intercept no longer has the typical meaning in regression equations (e.g., the predicted value when all independent variables have a value of zero) and instead is interpreted as the average unadjusted cluster mean value (alternatively, adjusted by any non-CWC covariates included in the model). The "Results and Discussion" section of Investigation 1 provides a more thorough discussion on how a more meaningful intercept is used to provide plotted predicted values.

Competing Model Comparison and Assumption Checking

The initially specified model was compared against alternative, more parsimonious, models that could also be used to evaluate the research hypotheses. For example, three-way interactions were hypothesized for purchase intentions, but only two-way interactions were specified for retransmissions and seek information intentions, thus suggesting that three-way interactions may be excluded from the latter two models. For each of the three dependent variables, nine models were compared with one another. Three random effects models (intercept only, intercept and valence only, and all main effects) were crossed with three levels of coefficients (main effects only, two-way interactions, and three-way interactions). Table 10 reports the log likelihood (LL), number of estimated parameters (k), Bayesian information criterion (BIC), and Akaike information criterion (AIC) are reported for all models. The results of this investigation demonstrate that the largest improvements in model fit can be attributed to the least restrictive specification of random slopes (all main effects allowed to randomly vary across brands). Much smaller improvements in model fit were attributed to the inclusion of higher-order effects into the models. Although both relative goodness-of-fit indexes clearly signal a preference for models with the most random slopes, there is inconsistency when it comes to preferring models with main, second-order, or third-order effects. The BIC favors models with fewer interactions, which is unsurprising, because it has a more severe punitive component for additional parameters than the AIC. The BIC suggests the two-way interaction model for purchase intentions, and the main effect only models for the other two dependent variables. In contrast, the AIC favors three-way interaction models for purchase intentions and seek information intentions and the two-way interaction model for retransmission intentions. According to these considerations, the retained models for each of the dependent variables were

models with the lowest higher-order interactions retained that still allowed for explicit evaluation of the research hypotheses (three-way interactions for purchase intentions and two-way interactions for the other two models).

Another important consideration in model selection is to investigate how robust model parameters are to the alternative proposed specifications. If parameters remain stable across different specifications, there is less concern that the final models were merely cherry-picked because of results favorable with the research hypotheses. Table 11 depicts the regression coefficients for all models with main effect random slopes but different levels of higher-order interactions specified. This comparison illustrates that the second-order interaction coefficients remain consistent regardless of whether the model includes the third-order interactions. Likewise, the main effects remain stable regardless of the number of interactions. Table 12 presents the fixed effect model parameters across the three specifications of random slopes. In this instance, the parameters vary somewhat more across the random slope specifications than that illustrated in Table 11, though the direction and significance level of parameters remain consistent.

Table 10: Model Comparison Across Varying Interaction and Random Slopes Specification

Interactions	Random Slopes	LL	k	BIC	AIC
Purchase Intentions					
Main effects only	Intercept only	–344445.0	31	689266.5	688952.0
	+ Valence	–339961.0	40	680407.8	680001.9
	+ Offline and Social Tie	–338159.1	58	677022.7	676434.2
+ 2-way interactions	Intercept only	–344271.2	42	689052.6	688626.4
	+ Valence	–339800.6	51	680220.8	679703.3
	+ Offline and Social Tie	–338006.5	69	676851.1	676150.9
+ 3-way interactions	Intercept only	–344273.7	48	689130.5	688643.4
	+ Valence	–339803.1	57	680298.5	679720.2
	+ Offline and Social Tie	**–337997.8**	**75**	**676906.7**	**676145.7**
Retransmission Intentions					
Main effects only	Intercept only	–343556.2	31	687489.0	687174.4
	+ Valence	–340785.7	40	682057.4	681651.5
	+ Offline and Social Tie	–339036.6	58	678777.7	678189.2
+ 2-way interactions	Intercept only	–343533.6	42	687577.4	687151.2
	+ Valence	–340757.5	51	682134.5	681617.0
	+ Offline and Social Tie	**–339015.8**	**69**	**678869.8**	**678169.6**
+ 3-way interactions	Intercept only	–343528.7	48	687640.4	687153.3
	+ Valence	–340752.8	57	682198.0	681619.6
	+ Offline and Social Tie	–339012.1	75	678935.2	678174.2
Seek Information Intentions					
Main effects only	Intercept only	–369151.5	31	738679.6	738365.0
	+ Valence	–366415.0	40	733315.8	732909.9
	+ Offline and Social Tie	–364428.1	58	729560.6	728972.1
+ 2-way interactions	Intercept only	–369097.6	42	738705.3	738279.2
	+ Valence	–366360.3	51	733340.0	732822.5
	+ Offline and Social Tie	**–364381.2**	**69**	**729600.5**	**728900.3**
+ 3-way interactions	Intercept only	–369087.2	48	738757.5	738270.5
	+ Valence	–366349.0	57	733390.5	732812.1
	+ Offline and Social Tie	–364372.3	75	729655.4	728894.4

Models selected for hypotheses evaluation are in boldface.

Table 11: Hierarchical Model Regression Comparison: Comparison of Fixed Effect Coefficients across Different Higher-Order Interaction Specifications

		Purchase Intentions			Retransmission Intentions			Seek Info Intentions		
		Main Effects Only	2-way Interactions	3-way Interactions	Main Effects Only	2-way Interactions	3-way Interactions	Main Effects Only	2-way Interactions	3-way Interactions
$\gamma_{0,0}$	Intercept	7.39 (.061)***	7.39 (.061)***	7.39 (.061)***	7.34 (.038)***	7.34 (.038)***	7.34 (.038)***	5.82 (.059)***	5.82 (.059)***	5.82 (.059)***
$\gamma_{1,0}$	Positive (Valence)	1.63 (.086)***	1.63 (.086)***	1.63 (.086)***	1.79 (.087)***	1.79 (.087)***	1.79 (.087)***	1.70 (.093)***	1.70 (.093)***	1.70 (.093)***
$\gamma_{2,0}$	Negative (Valence)	–2.63 (.162)***	–2.64 (.162)***	–2.64 (.162)***	.63 (.152)***	.63 (.152)***	.63 (.152)***	–.82 (.155)***	–.82 (.155)***	–.82 (.155)***
$\gamma_{3,0}$	Mixed (Valence)	–.29 (.105)**	–.29 (.105)**	–.29 (.105)**	.78 (.106)***	.78 (.106)***	.78 (.106)***	.50 (.110)***	.51 (.110)***	.50 (.110)***
$\gamma_{4,0}$	Offline (Channel)	.10 (.048)*	.11 (.048)*	.11 (.048)*	.08 (.054)	.08 (.054)	.09 (.054)	–.41 (.061)***	–.40 (.061)***	–.40 (.061)***
$\gamma_{5,0}$	Strong (Social Tie)	.55 (.030)***	.55 (.030)***	.55 (.030)***	.17 (.032)***	.17 (.032)***	.17 (.032)***	.26 (.041)***	.26 (.041)***	.26 (.041)***
$\gamma_{6,0}$	Expert (Social Tie)	.77 (.075)***	.77 (.075)***	.77 (.076)***	.37 (.075)***	.37 (.075)***	.37 (.075)***	.79 (.088)***	.79 (.088)***	.79 (.088)***
$\gamma_{7,0}$	Positive × Offline		.15 (.049)**	.13 (.050)**		.32 (.050)***	.31 (.050)***		.06 (.057)	.09 (.057)
$\gamma_{8,0}$	Negative × Offline		–.51 (.065)***	–.53 (.065)***		.37 (.066)***	.36 (.066)***		–.33 (.075)***	–.31 (.075)***
$\gamma_{9,0}$	Mixed × Offline		–.17 (.056)**	–.20 (.057)***		.18 (.057)**	.18 (.057)**		.04 (.065)	.06 (.065)
$\gamma_{10,0}$	Positive × Strong		–.21 (.027)***	–.21 (.027)***		.03 (.027)	.03 (.027)		–.13 (.031)***	–.13 (.031)***
$\gamma_{11,0}$	Negative × Strong		–.23 (.037)***	–.23 (.037)***		.00 (.037)	.00 (.037)		–.17 (.043)***	–.16 (.043)***
$\gamma_{12,0}$	Mixed × Strong		–.15 (.031)***	–.15 (.031)***		.05 (.031)	.05 (.031)		–.06 (.036)	–.06 (.036)
$\gamma_{13,0}$	Positive × Expert		–.62 (.069)***	–.60 (.070)***		–.28 (.070)***	–.26 (.070)***		–.43 (.080)***	–.47 (.080)***
$\gamma_{14,0}$	Negative × Expert		–.80 (.097)***	–.78 (.098)***		–.21 (.098)*	–.18 (.099)		–.26 (.112)*	–.26 (.113)*
$\gamma_{15,0}$	Mixed × Expert		–.31 (.083)***	–.28 (.084)***		–.13 (.084)	–.12 (.084)		–.01 (.096)	–.05 (.096)
$\gamma_{16,0}$	Strong × Offline		.12 (.038)**	.12 (.039)**		.06 (.039)	.06 (.039)		.25 (.044)***	.24 (.045)***
$\gamma_{17,0}$	Expert × Offline		.31 (.091)***	.33 (.091)***		.22 (.091)*	.23 (.092)**		.24 (.104)*	.21 (.105)*
$\gamma_{18,0}$	Positive × Offline*Strong			–.13 (.121)			.07 (.122)			.06 (.140)
$\gamma_{19,0}$	Negative × Offline × Strong			–.02 (.160)			–.23 (.161)			.36 (.184)
$\gamma_{20,0}$	Mixed × Offline × Strong			–.36 (.136)**			.21 (.137)			.03 (.157)
$\gamma_{21,0}$	Positive × Offline × Expert			.54 (.261)*			.47 (.263)			–1.10 (.300)***
$\gamma_{22,0}$	Negative × Offline × Expert			.61 (.359)			.77 (.362)*			.09 (.414)
$\gamma_{23,0}$	Mixed × Offline × Expert			.47 (.303)			.57 (.305)			–.87 (.349)*
	Model Fit									
	LL (k)	–338159 (58)	–338006 (69)	–337997 (75)	–339036 (58)	–339015 (69)	–339012 (75)	–364428 (58)	–364381 (69)	–364372 (75)
	BIC	677022.7	676851.1	676906.7	678777.7	678869.8	678935.2	729560.6	729600.5	729655.4
	AIC	676434.2	676150.9	676145.7	678189.2	678169.6	678174.2	728972.1	728900.3	728894.4

Covariates identified in Equation 1 were included in model but results are withheld from this table. Models reported here allow intercept and main effects to vary freely across brands.
* *p* <.05, two-tailed.; ** *p* < .01, two-tailed.; *** *p* < .001, two-tailed.

Table 12: Hierarchical Model Regression Comparison: Comparison of Fixed Effect Coefficients Across Different Random Slope Specifications

		Purchase Intentions			Retransmission Intentions			Seek Information Intentions		
		Intercept Random	Intercept and Valence Random	All Main Random	Intercept Random	Intercept and Valence Random	All Main Random	Intercept Random	Intercept and Valence Random	All Main Random
$\gamma_{0,0}$	Intercept	7.40 (.063)***	7.40 (.063)***	7.39 (.061)***	7.34 (.039)***	7.33 (.039)***	7.34 (.038)***	5.82 (.059)***	5.82 (.059)***	5.82 (.059)***
$\gamma_{1,0}$	Positive (Valence)	1.58 (.010)***	1.62 (.087)***	1.63 (.086)***	1.78 (.010)***	1.79 (.085)***	1.79 (.087)***	1.71 (.012)***	1.71 (.094)***	1.70 (.093)***
$\gamma_{2,0}$	Negative (Valence)	–2.69 (.016)***	–2.64 (.160)***	–2.64 (.162)***	.60 (.016)***	.63 (.151)***	.63 (.152)***	–.83 (.018)***	–.81 (.155)***	–.82 (.155)***
$\gamma_{3,0}$	Mixed (Valence)	–.34 (.013)***	–.29 (.107)**	–.29 (.105)**	.77 (.013)***	.78 (.106)***	.78 (.106)***	.50 (.014)***	.51 (.112)***	.51 (.110)***
$\gamma_{4,0}$	Offline (Channel)	.06 (.015)***	.06 (.015)***	.11 (.048)*	.06 (.015)***	.05 (.015)***	.08 (.054)	–.38 (.017)***	–.38 (.017)***	–.40 (.061)***
$\gamma_{5,0}$	Strong (Social Tie)	.53 (.008)***	.52 (.008)***	.55 (.030)***	.19 (.008)***	.19 (.008)***	.17 (.032)***	.27 (.010)***	.27 (.010)***	.26 (.041)***
$\gamma_{6,0}$	Expert (Social Tie)	.83 (.024)***	.82 (.023)***	.77 (.076)***	.43 (.024)***	.43 (.024)***	.37 (.075)***	.70 (.028)***	.70 (.027)***	.79 (.088)***
$\gamma_{7,0}$	Positive × Offline	.12 (.050)*	.13 (.049)**	.13 (.050)**	.30 (.050)***	.32 (.049)***	.32 (.050)***	.02 (.057)	.03 (.056)	.06 (.057)
$\gamma_{8,0}$	Negative × Offline	–.57 (.066)***	–.51 (.065)***	–.53 (.065)***	.34 (.066)***	.37 (.065)***	.37 (.066)***	–.39 (.075)***	–.37 (.074)***	–.33 (.075)***
$\gamma_{9,0}$	Mixed × Offline	–.25 (.058)***	–.21 (.056)***	–.20 (.057)***	.12 (.057)*	.16 (.056)**	.18 (.057)**	–.05 (.065)	–.02 (.064)	.04 (.065)
$\gamma_{10,0}$	Positive × Strong	–.25 (.028)***	–.21 (.027)***	–.21 (.027)***	.03 (.028)	.03 (.027)	.03 (.027)	–.13 (.032)***	–.13 (.031)***	–.13 (.031)***
$\gamma_{11,0}$	Negative × Strong	–.30 (.038)***	–.24 (.037)***	–.23 (.037)***	–.03 (.038)	–.01 (.038)	.00 (.037)	–.17 (.044)***	–.17 (.043)***	–.17 (.043)***
$\gamma_{12,0}$	Mixed × Strong	–.20 (.032)***	–.15 (.031)***	–.15 (.031)***	.03 (.032)	.03 (.031)	.05 (.031)	–.06 (.037)	–.06 (.036)	–.06 (.036)
$\gamma_{13,0}$	Positive × Expert	–.69 (.070)***	–.69 (.068)***	–.60 (.070)***	–.31 (.069)***	–.33 (.068)***	–.28 (.070)***	–.39 (.079)***	–.41 (.078)***	–.43 (.080)***
$\gamma_{14,0}$	Negative × Expert	–.78 (.098)***	–.80 (.096)***	–.78 (.098)***	–.18 (.097)	–.18 (.096)	–.21 (.098)*	–.12 (.111)	–.16 (.110)	–.26 (.112)*
$\gamma_{15,0}$	Mixed × Expert	–.34 (.084)***	–.37 (.082)***	–.28 (.084)***	–.14 (.083)	–.16 (.082)*	–.13 (.084)	.04 (.096)	.01 (.094)	–.01 (.096)
$\gamma_{16,0}$	Strong × Offline	.10 (.039)**	.11 (.038)**	.12 (.039)**	.03 (.039)	.05 (.038)	.06 (.039)	.27 (.045)***	.28 (.044)***	.25 (.044)***
$\gamma_{17,0}$	Expert × Offline	.32 (.089)***	.30 (.087)***	.33 (.091)***	.16 (.089)	.19 (.087)*	.22 (.091)*	.16 (.101)	.16 (.100)	.24 (.104)*
$\gamma_{18,0}$	Positive × Offline × Strong	.01 (.122)	–.06 (.119)	–.13 (.121)						
$\gamma_{19,0}$	Negative × Offline × Strong	.07 (.162)	–.06 (.159)	–.02 (.160)						
$\gamma_{20,0}$	Mixed × Offline × Strong	–.14 (.138)	–.19 (.135)	–.36 (.136)**						
$\gamma_{21,0}$	Positive × Offline × Expert	.12 (.252)	.18 (.247)	.54 (.261)*						
$\gamma_{22,0}$	Negative × Offline × Expert	.02 (.351)	–.03 (.344)	.61 (.359)						
$\gamma_{23,0}$	Mixed × Offline × Expert	.25 (.297)	.28 (.290)	.47 (.303)						
	Model Fit									
	LL (k)	–344273 (48)	–339803 (57)	–337997 (75)	–343533 (42)	–340757 (51)	–339015 (69)	–369097 (42)	–366360 (51)	–364381 (69)
	BIC	689130.5	680298.5	676906.7	687577.4	682134.5	678869.8	738705.3	733340.0	729600.5
	AIC	688643.4	679720.2	676145.7	687151.2	681617.0	678169.6	738279.2	732822.5	728900.3

Covariates identified in Equation 1 were included in model but results are withheld from this table. Models reported here display the order of interactions used to evaluate the hypotheses.
* -*p* <.05, two-tailed.; ** -*p*<.01, two-tailed.; *** *p*<.001, two-tailed.

The assumption of normally distributed errors (for both overall model and the random effects) was evaluated in a series of ways. According to the recommendation of Cohen and Cohen (2003, p. 141) that "graphical examination helps reveal the magnitude and nature of any non-normality in the residuals, information that is nearly always far more useful than the significance or nonsignificance of a formal statistical test," extensive visual examination was used. For example, Figure 9 depicts histograms with overlaid normal distributions of the random deviations of the regression coefficients allowed to vary randomly across brands. This serves as a visual inspection of the assumed normal distribution of the random effect residuals. All residuals appear approximately normal, though the distributions may be slightly more leptokurtic than a normal distribution. Figure 10 depicts the random effect residuals plotted against the predicted values for the three dependent variables. The residuals in all cases appear homoskedastic. All scatterplots show three main elliptical clumps of predicted values, by virtue of WOM valence having such a large and dominant main effect on the predictions of the dependent variables. (Negative WOM represents one clump, positive another, and mixed and neutral a third.) Finally, Figure 11 depicts Q-Q plots of the level 1 residual errors. There is departure from normality on the left tail of the normal distribution: The models tend to have larger negative residuals than expected (e.g., the predictions tends to be positively biased). A closer inspection of the predicted values indicates that the models may tend to perform poorly at predicting extremely low value responses from BrandChat respondents (e.g., 0, 1, 2).

Inspecting the model assumptions suggests that there are some small violations of assumptions. However, a review of literature about the impact of violations of multilevel modeling assumptions (e.g., Yuan and Bentler 2002, 2005) indicates that normal theory-based inference is often valid even with nonnormal hierarchical data. The current assessment is judged

to be not so severe as to threaten the validity of interpretation of coefficients for the research hypotheses.

Figure 9: Histograms of Random Error Components for Purchase, Retransmission, and Seek Information Intentions

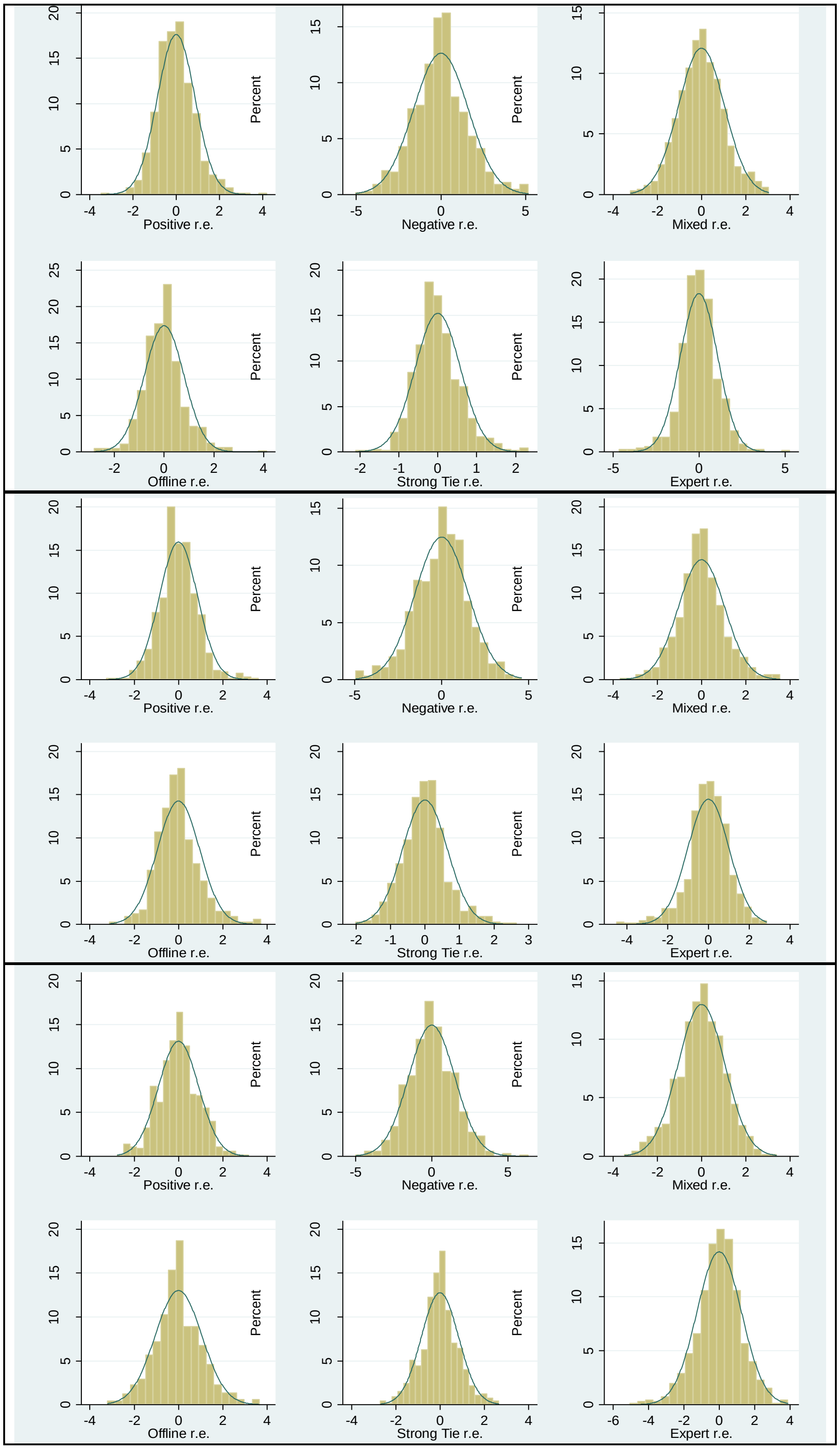


Figure 10: Plots of Random Effects Residuals Across Predicted Values: Purchase Intentions, Retransmission, and Seek Information

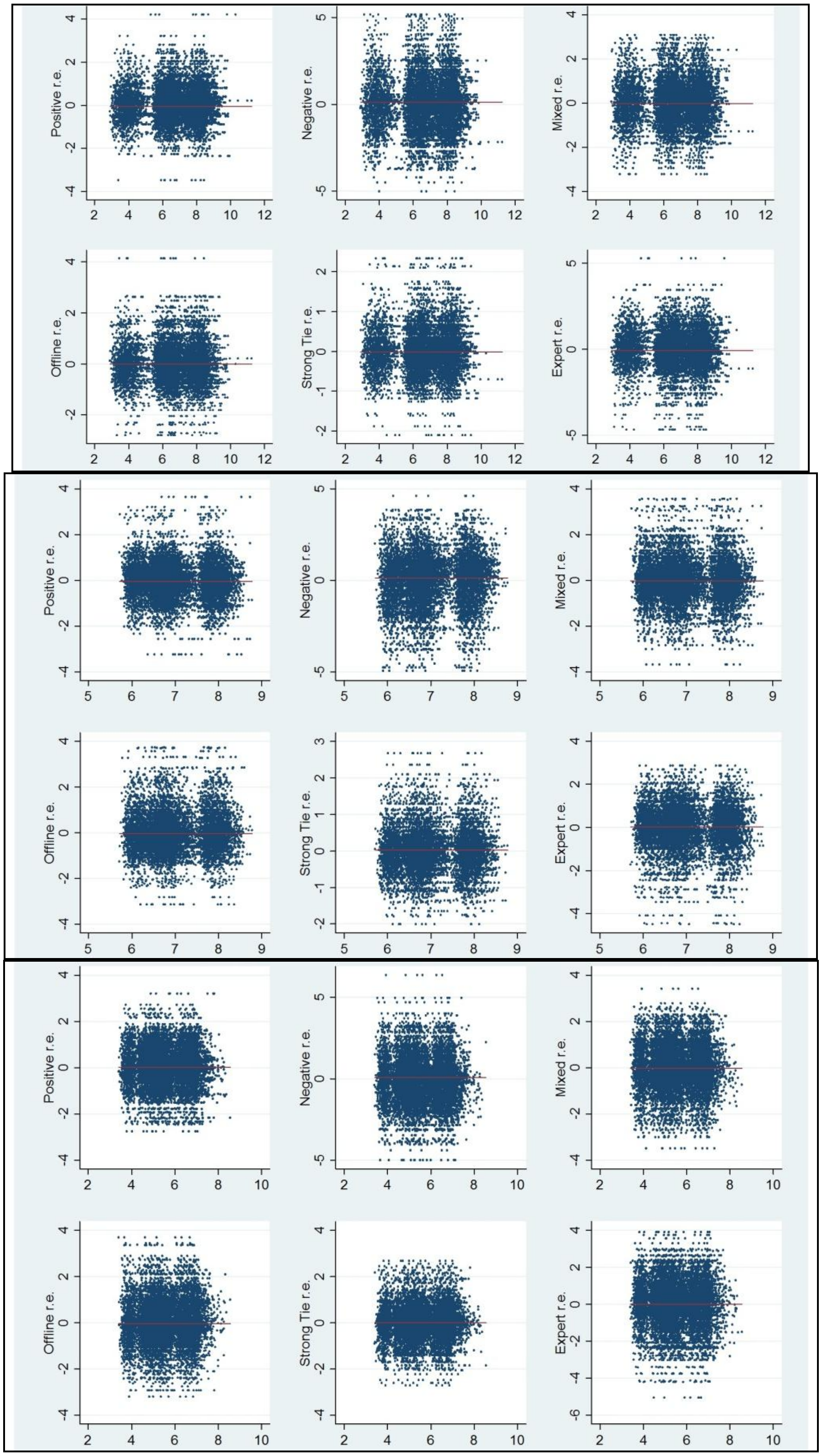
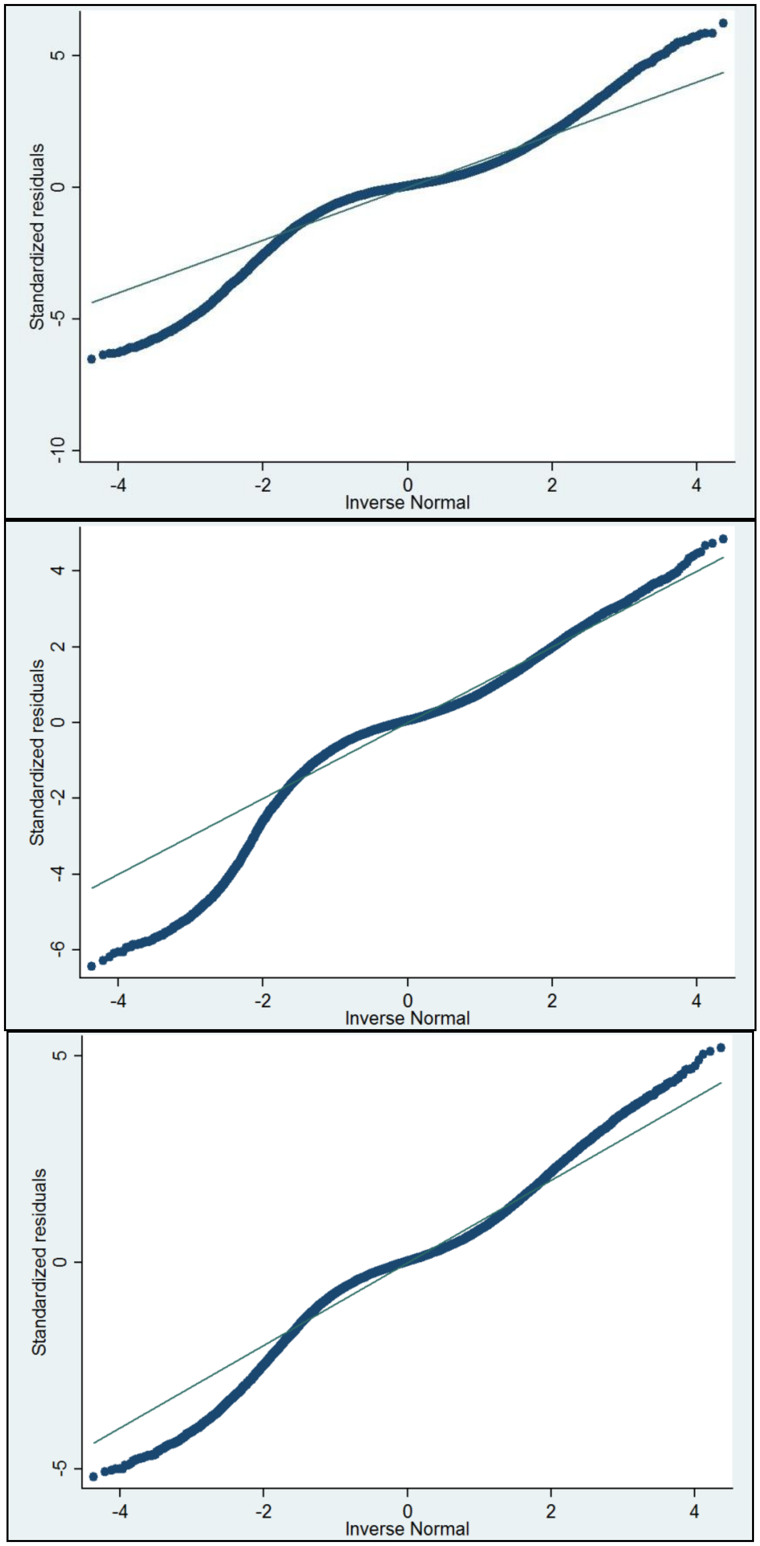


Figure 11: Q-Q Plots of Level One Residuals for Purchase, Retransmission, and Seek Information Intentions



The Degree of Clustering Within Brands

Thus far, the discussion has simply presumed that allowing the intercept and slope variances to vary across brands is reasonable, though no specific rationale for this treatment has been provided. In this section, the issue of within-brand clustering is investigated in greater detail and presented in two ways: through the intraclass correlation of the dependent variables and the design effects associated with the mean variance of the dependent variables. The intraclass correlation (ICC) indicates the degree of clustering (e.g., nonindependence) within brands on the three dependent variables. For example, the ICC for the intent to purchase dependent variable was calculated for the two-level model using the following formula:

$$ICC_{purchase} = \frac{\tau_{brand}}{\tau_{brand} + \sigma_{\epsilon}^{2}}$$

where τ_{brand} is the amount of variance in the mean level of intent to purchase at the brand level (level 2); σ^2_ε is the WOM conversation level (level 1) residual variance (Shrout and Feiss 1979); and $ICC_{purchase}$ represents the degree of correlation for intent to purchase scores within the same brand. Table 13 reports the results from the two-level hierarchical model used to derive the variance components used to estimate the ICC. $ICC_{purchase}$ is equal to .207. meaning an estimated 20.7% in the variation in the intent to purchase dependent variable is attributable to systematic clustering within brands. ICC_{resend} is equal to .067, indicating that 6.7% of the variation in intentions to retransmit the WOM message is attributable to systematic clustering within brands. $ICC_{seekinfo}$ is equal to .098, which means that 9.8% of the variation in intentions to seek additional information about the brand is attributable to within-brand clustering. The much larger ICC for purchase intentions than for retransmission intentions could be because the act of

actually purchasing a brand is highly contingent on prior knowledge and attitudes about a particular brand (thus, a relatively large ICC) and brand-specific characteristics such as price. In other words, intentions to purchase a brand are unlikely to be solely attributable to a single WOM conversation and may be expected to be informed by general patterns of prior knowledge and brand attitudes inside the consumer population. In contrast, intentions to merely retransmit the content of a WOM conversation has less to do with specific characteristics about a given brand and is instead determined more so by the particular content and characteristics of the actual conversation (thus, a relatively low ICC). In other words, the relatively low-cost activity of retransmitting the content of a WOM conversation can be motivated solely by a single conversation and has less to do with prior knowledge and beliefs of a particular brand.

Design effects (DEFF) are a concept usually applied to complex survey designs, but the underlying concept can be illustrative in the present case as well. I define DEFF as the ratio of the design-based variance (in this case, the strata is analogous to brands) of a variable to the hypothetical variance if simple random sampling had been used (in this case, as though every WOM conversation was for a unique brand) (StataCorp 2009). Table 13 also reports the DEFF of each dependent variable. These results reinforce that not accounting for the within-brand clustering would drastically overstate the statistical power of this large sample, because the DEFF ranged from 20.2 (retransmission intentions) to 60.4 (purchase intentions) times the variance if the sample was selected randomly (roughly interpretable in this instance as if each observation was for a unique brand).

Another source of potential clustering is at the BrandChat respondent level. That is, responses to the dependent variables tend to be more correlated within a respondent. Limitations in the BrandChat data extraction interface made it impossible to both extract all the conversation

characteristics required for analysis and identify which conversations were linked to the same respondent. However, this potential issue is unlikely to be a limitation for three reasons. First, the BrandChat system is a rotating panel, so there is no reason to suspect any respondent had multiple opportunities across time to respond. Second, the BrandChat system automatically whittles down detailed WOM questions in such a way that no single respondent could possibly provide detail on more than 10 WOM conversations for the type of data used in this analysis. Third, a raw data subset for three months (October 2007, October 2008, and October 2009) of BrandChat data was provided for a different analysis, and this data set had the capability to uniquely identify both respondent and brand conversations. Analysis of this data demonstrated that the mode of detailed WOM conversation for a respondent was 1 (thus, no threat of within-respondent clustering) and only a tiny fraction of respondents (< 5%) had more than five conversations.

In summary, the hierarchical models do not appear to drastically violate the underlying assumptions, and allowing for brand-level random effects drastically improves model fit. On the basis of these considerations motivating the model specification, the next section presents the hypotheses results and discussion for the models.

Table 13: Intraclass Correlations and Design Effects

		Intent to Buy	Intent to Resend	Intent to Seek Information
	Fixed-Effects (Level 1)	Coefficient (SE)	Coefficient (SE)	Coefficient. (SE)
γ_{00}	Intercept	7.52 (.038)	7.51 (.018)	6.06 (.026)
	Random-Effects Parameters	Estimate (SE)	Estimate (SE)	Estimate (SE)
	BRAND (level 2)			
τ_{brand}	variance (intercept)	.92 (.053)	.19 (.012)	.40 (.025)
σ_{ε}^{2}	variance (residual)	3.94 (.013)	2.66 (.009)	3.69 (.012)
	ICC	20.7%	6.7%	9.8%
	LL model	–397944.6	–360531.7	–391515.9
	AIC	795895.2	721069.4	783037.9
	BIC	795925.6	721099.8	783068.4
	Design Effects			
	DEFF	60.4	20.2	28.1

Results: Purchase Intentions

Table 14 summarizes the parameter estimates of the model, Table 15 displays the covariances of the random effects, and Table 16 presents the results of the hypotheses tests. $H_{1purchase}$ states that WOM valence would have a matching directional effect on purchase intentions. In support of $H_{1purchase}$, positive WOM was associated with an expected 1.63 unit ($p < .001$) increase in purchase intentions for a particular brand when compared with neutral sentiment about the brand. Negative WOM was associated with a 2.64 unit ($p < .001$) decrease in purchase intentions compared with neutral brand sentiment, also in support of $H_{1purchase}$. $H_{1purchase}$ was fully supported.

$H_{2purchase}$ states that the absolute effect of negative sentiment would be greater than the absolute effect of positive WOM on purchase intentions. A test of the linear combination of the positive and negative population regression coefficients ($\gamma_{1,0}$ and $\gamma_{2,0}$) was negative and significantly different from zero ($p < .001$), in support of $H_{2purchase}$. This result suggests that while positive WOM about brands is more prevalent, an individual negative episode is expected to have a greater effect than an individual positive WOM episode.

In addition to results about positive and negative WOM valence, the main effect for mixed sentiment about the brand on purchase intentions was significantly less ($\gamma_{3,0} = –.27$, $p < .001$) than neutral WOM about a brand. Although not specifically hypothesized, this result may be further evidence that negative sentiment has a disproportionately greater effect on purchase intentions (e.g., when a conversation has a blend of positive and negative sentiment, the negative sentiment dominates and thus results in mixed sentiment having a negative effect compared with neutral WOM).

It is also noteworthy that the variance of positive and negative WOM across brands ($\tau_{1,1}$ and $\tau_{2,1}$) are substantial compared with their standard errors and that the variance of the negative WOM slope is particularly substantial ($\tau_{2,1}$ = 3.18, SE = .233). This suggests that the extent to which a particular negative WOM episode influences purchase relative to a neutral sentiment varies substantially across particular brands.

$H_{3purchase}$ states that the channel of the WOM conversation will interact with the valence of the WOM conversation on purchase intentions such that offline WOM will cause positive WOM to have an even greater positive effect on purchase intentions and negative WOM to have an even more negative effect on purchase intentions. All hypotheses that proposed moderating effects (two-way and three-way interactions) were evaluated using the simple slopes approach with a formal slope difference t-test. The standard errors of the differences of the unstandardized slope coefficients were derived using the formulations of Dawson and Richter (2006). Dawson and Richter extended the two-way interaction derivation of Aiken and West's (1991) seminal work to the more generalized case of two and/or three-way interactions. $H_{3purchase}$ was fully supported, as the slope difference between positive, offline WOM and positive, online WOM was positive and significant ($\gamma_{7,0}$ = .13, p < .01) and the slope difference between negative, offline WOM and negative, online WOM was negative and significant ($\gamma_{8,0}$ = –.53, p < .001). In addition, the slope of mixed WOM is significantly more negative in an offline context than in an online context ($\gamma_{9,0}$ = –.20, p < .001). Thus, the negative effect of mixed valence WOM conversations is expected to have an even greater negative effect when the conversation occurs offline.

The channel of the WOM conversation was not expected to have a main effect on purchase intentions; however, unexpectedly, offline WOM had a positive influence on purchase

intentions compared with online WOM ($\gamma_{4,0}$ = .11, p < .05). Although this main effect was relatively small and there was a great deal of across-brand variance of this main effect ($\tau_{4,1}$ = .98, SE = .092), the significance of this population regression coefficient was unexpected. If anything, it seems reasonable that the online channel would have had a positive main effect on purchase intentions, given that, in general, the online channel creates a situation in which consumers can spontaneously make a brand purchase.

$H_{4purchase}$ involves how the influence of WOM valence on purchase intentions should be accentuated when it is between strong social ties. There was mixed support for this hypothesis. The slope difference between negative, strong-tie WOM and negative, weak-tie WOM was negative and significant ($\gamma_{11,0}$ = –.23, p < .001) indicating that the negative influence of negative WOM on purchase intentions is expected to be even greater when between strong social ties. However, the slope difference between positive, strong-tie WOM and positive, weak-tie WOM was also negative and significant ($\gamma_{12,0}$ = –.21, p < .001), implying that the effect of positive WOM from strangers is more impactful than would be expected for strong-tie positive WOM. Conversely, the main effect for strong social tie is positive, significant, and greater than the interaction terms ($\gamma_{5,0}$ = .55, p < .001). Thus, while the negative interaction coefficient indicates that negative WOM between strong social ties is more negative than would be expected by main effects alone, the unexpected positive main effect of strong social ties dominates the interaction effect. Similarly, the unexpected large positive main effect of strong social ties on purchase intentions dominates the interaction effect. In summary, there was partial support for $H_{4purchase}$, because the effect of negative WOM sentiment on purchase intentions is accentuated when between strong social ties, but the large positive main effect of strong social ties on purchase intentions was unexpected.

In addition to the positive main effect of strong social ties on purchase intentions compared with weak social ties, there was also a large, positive effect for experts compared with weak social ties ($\gamma_{6,0}$ = .75, p < .001). This large positive main effect dominates the significant negative interactions expert has with positive ($\gamma_{13,0}$ = -.60, p < .001), negative ($\gamma_{14,0}$ = –.78, p < .001) and mixed ($\gamma_{15,0}$ = –.28, p < .001) valence. There is substantial across-brand variation in the slope of expert social ties on purchase intention ($\tau_{6,1}$ = 2.06, SE = .201), suggesting that the degree a conversation with an expert directly influences brand purchase is particularly influenced by the given brand.

Finally, $H_{5purchase}$ states that the effect of positive and negative WOM on purchase intentions will be even further accentuated when it occurs between strong social ties in offline channels. This hypothesis was partially supported, as the slope difference between positive, strong-tie WOM in offline and online channels was positive but only marginally significant ($\Delta\beta$ = .10, p = .09) and the slope difference between negative, strong-tie WOM in offline and online channels was negative and highly significant ($\Delta\beta$ = –.53, p < .001). Even further, the difference in slopes between the effects of mixed WOM between strong ties in offline and online channels was negative and highly significant ($\Delta\beta$ = –.28, p < .001). This result suggests that receiving mixed signals from close social ties in offline settings tends to decrease intentions to purchase a brand even more. Because the results thus far have suggested that mixed sentiment acts similarly (but to a less intensive extent) as negative WOM when it comes to purchase intentions, it is perhaps not surprising that mixed sentiment from strong ties is further negatively amplified in offline contexts as well.

The covariances of the random effects provide some additional insight. The covariance between the intercept and positive valence is negative and is almost six times greater than its

standard error (–.21, SE = .042). This indicates that the higher the mean purchase intention score for a particular brand, the weaker the slope (e.g., a weaker positive effect) of positive WOM valence on purchase intentions compared with neutral WOM. The covariance of the random slopes of positive and negative valence is also positively correlated (.39), indicating that brands that tend to have particularly influential positive WOM are also somewhat insulated from the deleterious effects of negative WOM. (In other words, negative WOM will not have as large a negative effect.) This is also the case between mixed sentiment and positive sentiment ($r = .64$).

The only WOM-related covariate that was significant was the percentage of positive WOM a brand has across all WOM ($\gamma_{0,2} = .05$, $p < .001$). This result indicates that, all else being equal, WOM of any kind will tend to be linked with stronger purchase intentions as a brand has more overall positive WOM.

Table 14: Hierarchical Model Regression Results: – Purchase Intentions

	Dependent Variable: Purchase Intentions	β (SE)
γ0,0	Intercept	7.39 (.061)***
γ1,0	Positive (valence)	1.63 (.086)***
γ2,0	Negative (valence)	–2.64 (.162)***
γ3,0	Mixed (valence)	–.29 (.105)**
γ4,0	Offline (channel)	.11 (.048)*
γ5,0	Strong (social tie)	.55 (.030)***
γ6,0	Expert (social tie)	.77 (.076)***
γ7,0	Positive × Offline	.13 (.050)**
γ8,0	Negative × Offline	–.53 (.065)***
γ9,0	Mixed × Offline	–.20 (.057)***
γ10,0	Positive × Strong	–.21 (.027)***
γ11,0	Negative × Strong	–.23 (.037)***
γ12,0	Mixed × Strong	–.15 (.031)***
γ13,0	Positive × Expert	–.60 (.070)***
γ14,0	Negative × Expert	–.78 (.098)***
γ15,0	Mixed × Expert	–.28 (.084)***
γ16,0	Strong × Offline	.12 (.039)**
γ17,0	Expert × Offline	.33 (.091)***
γ18,0	Positive × Offline*Strong	–.13 (.121)
γ19,0	Negative × Offline*Strong	–.02 (.160)
γ20,0	Mixed × Offline*Strong	–.36 (.136)**
γ21,0	Positive × Offline*Expert	.54 (.261)*
γ22,0	Negative × Offline*Expert	.61 (.359)
γ23,0	Mixed × Offline*Expert	.47 (.303)
γ0,1	WOM Volume	.00 (.000)
γ1,1	WOM Volume × Positive	–.00 (.000)
γ2,1	WOM Volume × Negative	.00 (.000)
γ3,1	WOM Volume × Mixed	–.00 (.000)
γ0,2	Positive WOM %	.05 (.002)***
γ1,3	Positive WOM % × Positive	–.00 (.003)
γ2,4	Positive WOM % × Negative	.00 (.005)
γ3,5	Positive WOM % × Mixed	–.00 (.003)
σε2	Residual	2.01 (.006)
	Model Fit	
	LL (k)	–337997.8 (75)
	AIC	676145.6
	BIC	676906.7

* *p* <.05, two-tailed.; ** -*p*<.01, two-tailed.; *** *p*<.001, two-tailed.
Time covariates (γ24,0 – γ37,0) suppressed from output for space. Coefficients ranged from –.02 to .09.

Table 15: Variances and Covariances of Random Effects: Purchase Intentions

	Intercept	Positive	Negative	Mixed	Offline	Strong	Expert
Intercept	.47 (.027)	–.32	–.09	–.09	.18	–.10	–.25
Positive	–.21 (.031)	.93 (.068)	.39	.64	–.14	.06	.15
Negative	–.11 (.055)	.66 (.095)	3.18 (.233)	.41	.00	.02	.05
Mixed	–.07 (.036)	.71 (.07)	.85 (.116)	1.34 (.101)	–.06	–.02	.05
Offline	.12 (.036)	–.14 (.058)	.00 (.109)	–.06 (.069)	.99 (.093)	.02	.00
Strong	–.05 (.101)	.04 (.035)	.02 (.066)	–.02 (.043)	.01 (.042)	.45 (.036)	.42
Expert	–.25 (.055)	.21 (.091)	.13 (.172)	.09 (.111)	.00 (.098)	.41 (.068)	2.06 (.201)

Correlations reported on the upper diagonal.

Table 16: Summary of Hypotheses Results – Purchase Intentions

Hypothesis	Result	Additional Comments
$H_{1purchase}$	Fully supported	
$H_{2purchase}$	Fully supported	Negative WOM has a greater absolute effect on purchase intentions than positive WOM. In addition, mixed WOM also had a negative influence compared with neutral WOM. The across-brand variance of the effect of negative WOM was much greater than the effect of positive WOM.
$H_{3purchase}$	Fully supported	Positive and negative WOM occurring offline has an exacerbated influence on purchase intentions compared with online WOM. This moderation of WOM valence by the offline channel is particularly large for negative WOM. The negative effect of mixed valence WOM was also greater in offline channels.
$H_{4purchase}$	Partially supported	The unexpected dominating large positive main effect of strong social tie WOM on purchase intentions dominates the significant interactions between valence and social tie. Thus, despite the slope of positive WOM being attenuated by strong ties, the net impact is still greater than that of weak-tie WOM. In contrast, negative WOM is accentuated by strong ties, but the large positive main effect dominates this interaction and thus does not support the hypothesis. In addition, WOM from experts was particularly influential for purchases, particularly when the WOM was neutral or mixed.
$H_{5purchase}$	Partially supported	Negative WOM between strong social ties was even more negatively impactful when it occurred offline, in support of the hypothesis. However, the hypothesized accentuating effect of this three-way interaction was not significant for positive WOM. In addition, the negative influence of mixed WOM was even further accentuated when between strong social ties offline.

Discussion: Purchase Intentions

Figure 12 depicts the estimated value of intentions to purchase based on the fixed-effects portion of the model (i.e., ignoring within-brand variation or assuming variation from the B for a given brand = 0). Because the intercept for the CWC-centered regression ($\gamma_{0,0}$) depicts the expected mean for a given brand (and not the predicted value for y-hat when all variables equal 0, as is the more familiar intercept interpretation in multiple regression), it is necessary to select a more meaningful value for the intercept to aid in interpretation of the presented figure. The raw mean value of intentions to purchase when the WOM conversation was online, between weak social ties, and neutral in valence (i.e., when all dummy variables equaled 0) was selected as a useful reference (x-hat = 5.85 (.18)). It is important to note that selecting this value is somewhat arbitrary in the sense that regardless of the intercept value used for visual exposition, all mean differences between WOM characteristic groups is preserved (and thus the integrity of the hypotheses is maintained) regardless of the value selected to replace the intercept. Figure 12 (1) shows the WOM channel on the x-axis (offline/online), (2) uses solid lines to demonstrate strong social ties and dotted lines for weak social ties, and (3) depicts neutral valence with square endpoints, positive valence with triangle endpoints, and negative valence with circle endpoints. Expert WOM and mixed-valence WOM are not included in the figure, as neither were focal components of the present analysis and it was desirable to maintain an uncluttered presentation of the key findings.

Figure 12 illustrates that compared with neutral brand sentiment, the absolute effect of negative sentiment is greater than positive sentiment. Marketers often believe that negative information about an offering has a disproportionally harmful influence compared with positive

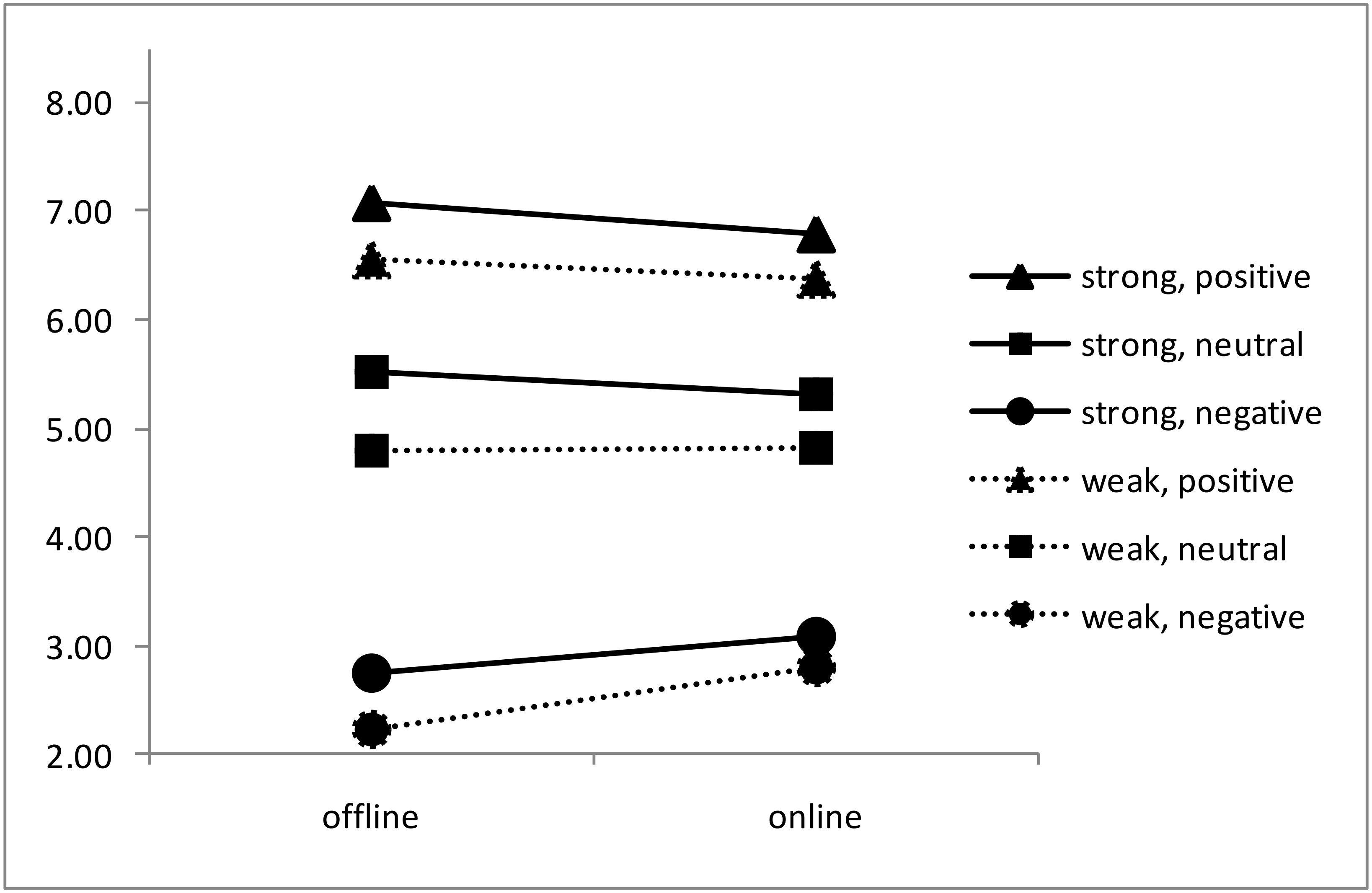
information. These results corroborate this sentiment in terms of noncommercial consumer-to-consumer personal communication as well. This is a novel insight in the context of consumer WOM, albeit one that is consistent with marketing insights into uneven consumer response to positive and negative sentiment. It is also important to note that this insight is the first to my knowledge to directly consider the impact of WOM about a brand on the WOM recipient. Thinking about positive and negative WOM in management tends to center on the (poorly supported) axiom that an unhappy customer may speak to many more people about their negative experience than they would have if they had a positive experience. Regardless of the veracity of such thinking, that axiom is a question of WOM *frequency*; these results speak to the actual influence a given WOM conversation has.

Moreover, it is clear that the valence of WOM has a greater effect on purchase intentions, making positive WOM even more effective at influencing purchase and making negative WOM even more damaging to a consumer's intentions to buy or try a brand. Although the interaction between channel and WOM valence is relatively small compared with the large main effect of WOM valence, these results serve to highlight that marketers overlooking more impactful offline WOM and only attending to online WOM are underestimating the positive brand benefits of positive WOM and the deleterious effect of negative WOM in offline channels. Although marketers do not tend to have formal systems in place to monitor WOM about their brands in general, when they do, the systems usually focus exclusively on online channels (presumably because tracking such sentiment online is a relatively less complicated affair given the prevalence of automated tools and services). Considering (1) the limited tracking of consumer WOM, (2) the evidence that suggests a much larger proportion of brand WOM occurs offline, and (3) the finding that the impact of offline WOM is greater than equivalent offline WOM (the

new insight from these analyses), these results further underscore that brand managers are likely drastically underestimating the true role of WOM in the performance of their brands.

The positive main effect of strong social ties dominating the interaction between its interactions (denoted in Figure 12 by the solid line representing strong tie for a particular valence type always above the dotted line representing weak ties) with WOM valence results in some unexpected results, inconsistent with expectations. The expectation was that the relative intensity of the social bond between actors would tend to exacerbate the effect of positive and negative WOM on purchase intentions by virtue of the expectation that brand-related sentiment would tend to be more trusted. However, this was not the case for negative WOM; intentions to buy or try a brand were actually slightly higher when the conversation was between strong social ties. It could be speculated that brand-related conversations between strong social ties may sometimes be only partly more relevant in the sense that discussion of a particular brand is generally of greater interest to the WOM actor (by virtue of the person with an opinion about the brand knowing the other party better), but the actual negative sentiment about the brand does not resonate. In such cases, negative WOM from a strong social tie could increase purchase intentions by virtue of tailored discussion of a particular brand dominating the effect of the negative sentiment about the brand.

Figure 12: Predicted Intention to Buy Score (Fixed Effects Only)



Results: Retransmission Intentions

Table 17 summarizes the parameter estimates of the model, and Table 18 presents the covariances of the random effects. Table 19 summarizes the results of the hypothesis tests. $H_{1retransmit}$ states that strong valence would positively influence retransmission intentions. This hypothesis was confirmed as positive valenced WOM conversations were associated with a 1.79 unit increase ($p < .001$) in retransmission intentions for a particular brand when compared with neutral WOM about the brand. Furthermore, negative WOM was associated with a .63 unit increase ($p < .001$) in retransmission intentions compared with neutral WOM. As further evidence that strong valence is an important factor determining retransmission, mixed-valence WOM also had a strong positive influence on retransmission intentions compared with neutral WOM ($\gamma_{3,0} = .78$, $p < .001$).

$H_{2retransmit}$ specified that positive WOM would have a greater positive influence on retransmission than negative WOM. A test of the linear combination of the positive valence population regression coefficient minus the negative valence population regression coefficient ($\gamma_{1,0}$ and $\gamma_{2,0}$) was positive and highly significant ($p < .001$). This result provides support for $H_{2retransmit}$. This result suggests that hearing about positive things about a brand is a much bigger catalyst for retransmission (e.g., "going viral") than is hearing negative things about a brand. However, hearing strong sentiment about a brand, even if such sentiment is mixed, is much more important than hearing neutral sentiment about a brand.

In addition to the fixed effects of the valence parameters, the variance of the valence parameters across brands ($\tau_{1,1}$, $\tau_{2,1}$, and $\tau_{3,1}$) contains additional insights. The slope of the negative valence direct effect on retransmission intentions varies the most across brands (2.84, SE = .213), suggesting that the extent to which negative sentiment influences transmission is

influenced heavily by the brand in question. The variance of positive valence across brands is the lowest of the three valence parameters (.92, SE = .070), indicating that the strong effect of positive sentiment on retransmission is more stable across brands than negative or mixed WOM (1.36, SE = .104). There is a strong correlation of these valence parameters (.53 to .77), which implies that when strong sentiment of any kind is particularly dominant (less dominant) over neutral WOM in inducing retransmission for a brand, the other types of WOM valence will also be even stronger (weaker) than neutral WOM.

$H_{3\ retransmit}$ states that the relative difficulty of retransmitting a message received offline compared with one received in an online channel would lead to offline WOM having a negative direct effect on retransmission intentions compared with online channels. This hypothesis was not supported, as the main effect of offline WOM was not significant ($p > .05$). There was substantial across brand variation in the regression coefficient estimate for offline WOM ($\tau_{4,1}$ = 1.34, SE = .119).

$H4_{retransmit}$ posited a positive main effect of WOM between strong social ties compared with WOM between weak social ties. This hypothesis was supported ($\gamma_{5,0} = .17$, $p < .001$). Compared with the variation for other main effects coefficients across brands, the variation for strong social ties was smaller ($\tau_{5,1} = .54$, SE = .043). In addition, WOM with an expert had an even greater positive main effect than that between strong social ties ($\gamma_{6,0} = .37$, $p < .001$), though the across-brand variation was substantial ($\tau_{6,1} = 1.93$, SE = .205).

$H_{5retransmit}$ states that the positive effect of valenced WOM on retransmission intentions is further accentuated when it occurred in an online channel. This hypothesis was not supported, as the difference in slopes between positive, offline WOM and positive, online WOM and negative,

offline WOM and negative, online WOM were both unexpectedly positive and highly significant (.32 and .37, respectively, both *p*s < .001), meaning that the positive main effect of valenced WOM on retransmission intentions would actually be *attenuated* when they occur in an online channel. This was also true in the case of mixed valenced WOM, as the interaction between mixed valence and offline WOM was also significant ($\gamma_{9,0}$ = .18, $p < .01$). This unexpected finding suggests that the positive intentions to retransmit WOM about a brand may not be increasingly influenced so much by the ease of retransmission afforded by online channels but is instead is positively influenced further by the additional rich content expected to be shared in communications occurring in richer channels (i.e., offline).

$H_{6retransmit}$ stated that strongly valenced WOM would be further accentuated when the conversation occurred between strong social ties. This hypothesis was not supported, as the slope differences between positive and negative WOM across weak ties and strong ties were not significant ($\gamma_{10,0}$ and $\gamma_{11,0}$, $p >.05$). In addition, the interaction between strong social ties and mixed valence was not significant ($\gamma_{12,0}$, $p > .05$).

The slope difference between positive, expert WOM and positive, weak-tie WOM was negative and significant ($\gamma_{13,0} = –.28$, $p < .001$) and was also significantly negative compared with positive strong-tie WOM ($p < .001$), suggesting that while expert opinion has a positive main effect on retransmission intentions, this effect is less than expected (attenuated) when the WOM was positive. This is also the case for negative WOM, but to a slightly lesser extent, as the slope difference is again significant compared with either weak-tie or strong-tie negative WOM ($p < .05$). The interaction between the offline channel and expert opinion was positive and significant ($\gamma_{17,0}$ = .22, $p < .05$), suggesting that the greater intention to retransmit a WOM message from an expert compared with WOM received from a weak social tie is even further

exacerbated when the conversation occurs in an offline channel. The interaction between offline WOM and strong social ties ($\gamma_{16,0}$) was not significant ($p > .05$).

Two WOM-related covariates were significant: the percentage of positive WOM a brand has across all WOM ($\gamma_{0,2} = .01$, $p < .001$) and the interaction between negative WOM and the percentage of WOM a brand has ($\gamma_{2,4} = –.01$, $p < .05$). This result indicates that, all else being equal, WOM of any kind, except negative WOM, will tend to be linked with stronger retransmission intentions as a brand has more overall positive WOM. This result suggests that brands with positive WOM will continue to propagate good, neutral, or mixed information are resistant to negative WOM propagating.

Table 17: Hierarchical Model Regression Results: Retransmission Intentions

	Dependent Variable: Retransmission Intentions	β (SE)
$\gamma_{0,0}$	Intercept	7.34 (.038)***
$\gamma_{1,0}$	Positive (Valence)	1.79 (.087)***
$\gamma_{2,0}$	Negative (Valence)	.63 (.152)***
$\gamma_{3,0}$	Mixed (Valence)	.78 (.106)***
$\gamma_{4,0}$	Offline (Channel)	.08 (.054)
$\gamma_{5,0}$	Strong (Social Tie)	.17 (.032)***
$\gamma_{6,0}$	Expert (Social Tie)	.37 (.075)***
$\gamma_{7,0}$	Positive × Offline	.32 (.050)***
$\gamma_{8,0}$	Negative × Offline	.37 (.066)***
$\gamma_{9,0}$	Mixed × Offline	.18 (.057)**
$\gamma_{10,0}$	Positive × Strong	.03 (.027)
$\gamma_{11,0}$	Negative × Strong	.00 (.037)
$\gamma_{12,0}$	Mixed × Strong	.05 (.031)
$\gamma_{13,0}$	Positive × Expert	–.28 (.070)***
$\gamma_{14,0}$	Negative × Expert	–.21 (.098)*
$\gamma_{15,0}$	Mixed × Expert	–.13 (.084)
$\gamma_{16,0}$	Strong × Offline	.06 (.039)
$\gamma_{17,0}$	Expert × Offline	.22 (.091)*
$\gamma_{0,1}$	WOM Volume	–.00 (.000)
$\gamma_{1,1}$	WOM Volume × Positive	–.00 (.000)
$\gamma_{2,1}$	WOM Volume × Negative	.00 (.000)
$\gamma_{3,1}$	WOM Volume × Mixed	–.00 (.000)
$\gamma_{0,2}$	Positive WOM %	.01 (.001)***
$\gamma_{1,3}$	Positive WOM % × Positive	.01 (.003)
$\gamma_{2,4}$	Positive WOM % × Negative	–.01 (.005)*
$\gamma_{3,5}$	Positive WOM % × Mixed	.00 (.003)
σ_{ε}^{2}	Residual	2.03 (.006)
	Model Fit	
	LL (k)	–339015.8 (69)
	AIC	681617.0
	BIC	682134.5

* *p* < .05, two-tailed. ; ** *p* < .01, two-tailed.; *** *p* < .001, two-tailed.
Time covariates (γ24,0 – γ37,0) suppressed from output for space. Coefficients ranged from –.02 to .09.

Table 18: Variance and Covariances of Random Effects: Retransmission Intentions

	Intercept	Positive	Negative	Mixed	Offline	Strong	Expert
Intercept	.17 (.011)	–.08	.10	.01	.15	–.16	–.10
Positive	–.03 (.019)	.92 (.070)	.57	.77	.00	–.06	.01
Negative	.07 (.034)	.92 (.098)	2.84 (.213)	.53	.10	–.10	–.04
Mixed	.00 (.024)	.86 (.075)	1.04 (.12)	1.36 (.105)	.06	–.06	–.09
Offline	.07 (.026)	.00 (.065)	.20 (.118)	.08 (.081)	1.34 (.12)	–.06	.01
Strong	–.05 (.105)	–.04 (.039)	–.12 (.068)	–.05 (.048)	–.11 (.053)	.54 (.043)	.31
Expert	–.06 (.036)	.01 (.092)	–.10 (.175)	–.15 (.117)	.01 (.116)	.32 (.075)	1.93 (.205)

Correlations reported on the upper diagonal.

Table 19: Summary of Hypotheses Results: Retransmission Intentions

Hypothesis	Result	Additional Comments
$H_{1retransmit}$	Fully supported	
$H_{2retransmi}$t	Fully supported	Positive WOM had a greater effect on retransmission intentions than negative WOM. In addition, mixed WOM also had a greater effect on retransmission intentions than neutral WOM. Sharing strong sentiment, especially when at least some of it is positive, is important to induce retransmission of WOM messages. However, the large across-brand variance of the impact of negative WOM on retransmission indicates that for some brands, negative WOM may be more impactful than positive WOM, though the strong positive correlation of positive and negative WOM parameters suggests that for the brands for which negative WOM is much more impactful, positive WOM will also be even more impactful.
$H_{3retransmit}$	Not supported	
$H_{4retransmit}$	Fully supported	WOM with strong social ties tends to directly influence more WOM retransmission than weak-tie WOM. In addition, WOM from experts is also influential at inducing additional WOM.
$H_{5retransmit}$	Not supported / Unexpected findings	In contrast with expectations, the offline channel tended to positively accentuate message retransmission. Despite the presumed ease of retransmission provided by easy access to an online channel, these results suggest that the message richness associated with offline channels may be an even more important contributor to motivating future message transmission.
$H_{6retransmit}$	Not supported	There was not a significant moderating influence of strong–social tie WOM on the positive influence of valenced WOM on message retransmission.

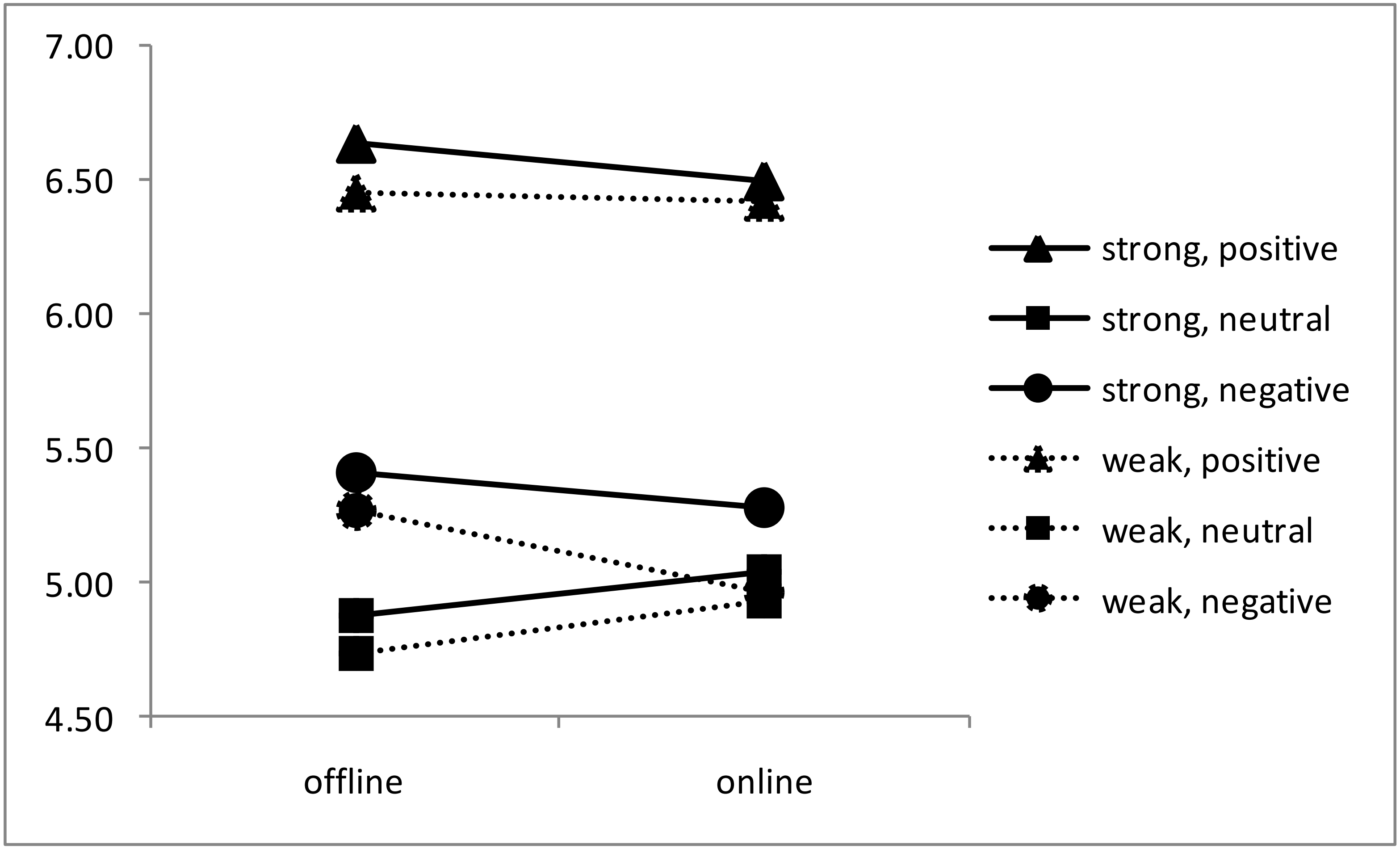
Discussion: Retransmission Intentions

Figure 13 depicts the estimated values of retransmission intentions based on fixed effects only (e.g., ignoring within-brand variation, assuming variation from the B for a given brand = 0). The intercept used to plot the estimated retransmission scores was the raw mean value of retransmission intentions when the WOM was between weak social ties, online, and neutral in valence (which is when all dummy variables equaled 0) (x-hat = 6.12 (.16)). Figure 13 (1) shows WOM channel on the x-axis (offline/online), (2) uses solid lines to demonstrate strong social ties and dotted lines for weak social ties, and (3) depicts neutral valence with square endpoints, positive valence with triangle endpoints, and negative valence with circle endpoints.

Compared with neutral brand sentiment, positive and negative sentiment both positively increase the intentions to retransmit the WOM message about a brand. It is also clear that positive sentiment about a brand is more likely to be transmitted than negative sentiment. This result is interesting and novel because it provides some insight into how the sentiment of a received transmission about a brand influences the capacity for brand WOM to go viral (e.g., be shared by a consumer when the consumer did not initiate the original sentiment). These results indicate that positive news about a brand is much more likely to be passed along to future audiences. Although the popular business press has put forth the notion that satisfied customers tell fewer people about their satisfaction than the many they tell when they are dissatisfied (Blackshaw 2008), these results suggest that the opposite is true when the sentiment about the brand is not generated directly from a personal experience.

Figure 13 also clearly demonstrates how offline WOM, regardless of sentiment, is more likely to be retransmitted than online WOM. Considering that the richness and depth of offline communications (suggesting increased likelihood of retransmission) was at tension with the relative ease of retransmitting online WOM (suggesting that online WOM may have greater retransmission tendency), it is noteworthy that there was a strong interaction between offline WOM and all forms of WOM valence. Finally, as indicated by the "strength of strong ties" notion, WOM is more likely to be retransmitted when the original message comes from a well-known other. It is important to note that this result does not contradict the "strength of weak ties" notion; it is simply consistent with expectations of strong tie communications. Indeed, the strength of weak ties argument directly acknowledges that, in general, information received from less-known others is more irrelevant and distrusted and thus unlikely to be retransmitted to future audiences. The strength of weak ties argument essentially claims that in the uncommon instance when a weak tie communication is sufficiently relevant and trusted, it is also likely that it is a novel insight ultimately retransmitted into a semi-closed network of strong ties.

Figure 13: Predicted Intention to Retransmit Score (Fixed Effects Only)



Results: Seek Information Intentions

Table 20 presents the parameter estimates of the model, and Table 21 shows covariances of the random effects. Table 22 summarizes the results of the hypothesis tests. $H1_{seekinfo}$ states that, compared with neutral WOM, positive WOM should have a positive effect on intentions to seek additional information and negative WOM would have a negative influence on intentions to seek additional information. The data strongly support $H_{1seekinfo}$: Positive WOM was associated with a 1.69-unit increase in intentions to seek additional information ($p < .001$) compared with neutral WOM, and negative WOM was associated with a .82-unit decrease ($p < .001$). In addition, mixed WOM had a positive influence on intentions to seek additional information about a brand ($\gamma_{3,0} = .51$, $p < .001$) compared with neutral information about a brand, suggesting that people will tend to seek additional information about a brand to reduce the ambiguity surrounding a conversation with mixed messages. The across-brand variance of the regression slope estimates for the WOM valence variables ($\tau_{1,1}$, $\tau_{2,1}$, $\tau_{3,1}$) were all substantial (1.05, SE = .081; 2.93, SE = .228; 1.46, SE = .115, respectively), though the across-brand variance for negative WOM was the largest. This suggests that the extent to which negative WOM influences intentions to seek additional information depends greatly on the particular brand. The strong positive correlation of the positive, negative, and mixed valence random effects parameters across brands (ranging .47 to .68) suggests that some brands motivate much more additional information search regardless of the valence of the WOM episode, while others tend to have lower levels of information search intention impact, regardless of the WOM valence.

$H_{2\ seekinfo}$ states that the absolute effect of positive WOM on intentions to seek additional information about a brand would be greater than the absolute effect of negative WOM. A test of

the linear combination of the positive and negative population regression coefficients ($\gamma_{1,0}$ and $\gamma_{2,0}$) was positive and significantly different from zero ($p < .001$), in support of $H_{2\ seekinfo}$.

$H_{3seekinfo}$ posits that people will be more likely to seek information about a brand discussed during a WOM conversation when the conversation occurred through an online medium. $H_{3\ seekinfo}$ was supported: Intentions to seek additional information were lower when the WOM conversation occurred in an offline channel ($\gamma_{4,0} = -.40$, $p < .001$). The across-brand variance of this slope estimate is large ($\tau_{4,1} = 1.65$, SE = .147).

$H_{4seekinfo}$ states that the reduced search cost associated with conversations occurring in an online channel would even further accentuate the positive direct effect of positive WOM on intentions to seek additional information and would attenuate the negative effect of negative WOM on intentions to seek additional information about a brand. There was partial support for this hypothesis. The slope difference between positive, offline WOM and positive, online WOM is not significant ($\gamma_{7,0} = .06$, $p > .05$), meaning that there is no support for the claim that the direct, positive effect of positive valenced WOM on information search intentions is accentuated when the conversation occurs in an online channel. The data support the online channel's attenuating effect on the negative effect of negative WOM on intentions to seek additional information: The slope difference between negative, online WOM and negative, offline WOM was negative and highly significant ($\gamma_{8,0} = -.33$, $p < .001$). The interaction between mixed-valence WOM and the offline channel was not significant ($\gamma_{9,0} = .04$, $p > .05$).

$H_{5seekinfo}$ states that WOM between strong social ties will interact with the valence of the WOM such that positive WOM will have less of a positive effect on intentions to seek additional information about a brand and will even further accentuate the negative effect of negative WOM

on intentions to seek information. This hypothesis was supported: The slope difference between positive, weak-tie WOM and positive, strong-tie WOM was negative and strongly significant ($\gamma_{10,0}$ = –.13, $p < .001$), which implies that positive WOM from strong ties has less of an impact on motivating additional information search. Furthermore, the slope difference between negative, weak-tie WOM and negative, strong-tie WOM was also negative and strongly significant ($\gamma_{11,0}$= –.17, $p < .001$). This implies that the negative influence of negative WOM on motivating additional information search is even greater when it is between strong ties than weak ties. This result indicates that respondents may be less inclined to verify positive or negative brand claims when they are made by a close social tie. However, there was an unexpected positive and significant main effect for strong social ties ($\gamma_{5,0}$ = .27, $p < .001$), which is greater than the absolute effect of either interaction. Thus, although in general strong–social tie WOM increases intentions to seek additional brand information when compared with weak–social tie WOM, this increase is not as strong when the WOM is valenced (positive or negative) as when it is neutral. In addition, the slope difference between mixed, weak-tie WOM and mixed, strong-tie WOM was not significant ($\gamma_{12,0}$ = –.06, $p > .05$). The across-brand variance for the main effect of strong social ties is relatively modest ($\tau_{5,1}$ = .88, SE = .067).

There is also a large positive main effect on intentions to seek additional information when the conversation about the brand was with an expert ($\gamma_{6,0}$ = .79, $p < .001$) suggesting that any brand-related information shared by an expert motivates additional information search about the brand. There was a negative interaction between positive valence WOM and experts ($\gamma_{13,0}$ = –.43, $p < .001$), implying that intentions to seek additional information when it is from an expert is somewhat tempered when the information shared about a brand is positive. The positive effect of brand information from an expert on intentions to seek information is also tempered when the

brand information is negative ($\gamma_{14,0}$ = –.26, $p < .05$). The interaction between mixed-valence and expert WOM was not significant ($\gamma_{15,0}$, $p > .05$).

Although not hypothesized, there was also a significant interaction between offline WOM and strong social ties ($\gamma_{16,0}$ = .25, $p < .001$) and offline WOM and experts ($\gamma_{17,0}$ = .24, $p < .05$). This implies that the positive effect of online WOM on intentions to seek additional information is tempered when the conversation is with an expert or strong social tie rather than a weak social tie. The only significant brand-related covariate was the percentage of positive WOM a brand has across all WOM ($\gamma_{0,2}$ = .01, $p < .001$). This result indicates that, all else being equal, WOM of any kind will tend to be linked with stronger seek information intentions, because a brand has more overall positive WOM.

Table 20: Hierarchical Model Results CWC – Dependent Variable: Seek Information

	Dependent Variable: Seek Information Intentions	β (SE)
$\gamma_{0,0}$	Intercept	5.82 (.059)***
$\gamma_{1,0}$	Positive (valence)	1.70 (.093)***
$\gamma_{2,0}$	Negative (valence)	–.82 (.155)***
$\gamma_{3,0}$	Mixed (valence)	.51 (.110)***
$\gamma_{4,0}$	Offline (channel)	–.40 (.061)***
$\gamma_{5,0}$	Strong (social tie)	.26 (.041)***
$\gamma_{6,0}$	Expert (social tie)	.79 (.088)***
$\gamma_{7,0}$	Positive × Offline	.06 (.057)
$\gamma_{8,0}$	Negative × Offline	–.33 (.075)***
$\gamma_{9,0}$	Mixed × Offline	.04 (.065)
$\gamma_{10,0}$	Positive × Strong	–.13 (.031)***
$\gamma_{11,0}$	Negative × Strong	–.17 (.043)***
$\gamma_{12,0}$	Mixed × Strong	–.06 (.036)
$\gamma_{13,0}$	Positive × Expert	–.43 (.080)***
$\gamma_{14,0}$	Negative × Expert	–.26 (.112)*
$\gamma_{15,0}$	Mixed × Expert	–.01 (.096)
$\gamma_{16,0}$	Strong × Offline	.25 (.044)***
$\gamma_{17,0}$	Expert × Offline	.24 (.104)*
$\gamma_{0,1}$	WOM Volume	–.00 (.000)
$\gamma_{1,1}$	WOM Volume × Positive	.00 (.000)
$\gamma_{2,1}$	WOM Volume × Negative	.00 (.000)
$\gamma_{3,1}$	WOM Volume × Mixed	–.00 (.000)
$\gamma_{0,2}$	Positive WOM %	.01 (.001)***
$\gamma_{1,3}$	Positive WOM % × Positive	.00 (.003)
$\gamma_{2,4}$	Positive WOM % × Negative	.01 (.006)
$\gamma_{3,5}$	Positive WOM % × Mixed	.00 (.004)
σ_{ε}^{2}	Residual	2.66 (.008)
	Model Fit	
	LL (k)	–364381.2 (69)
	AIC	728900.3
	BIC	729600.5

* $p < .05$, two-tailed.; ** $p < .01$, two-tailed.; *** $p < .001$, two-tailed.
Time covariates (γ24,0 – γ37,0) suppressed from output for space. Coefficients ranged from .03 to .38.

Table 21: Covariances of Model - Random Effects – Dependent Variable: Seek Information Message

	Intercept	Positive	Negative	Mixed	Offline	Strong	Expert
Intercept	.41 (.025)	–.03	–.10	–.03	.14	.01	–.02
Positive	–.02 (.031)	1.05 (.081)	.50	.68	–.02	–.08	.04
Negative	–.11 (.054)	.87 (.106)	2.93 (.228)	.47	–.04	–.11	–.03
Mixed	–.03 (.038)	.84 (.082)	.98 (.126)	1.46 (.115)	–.04	–.02	–.07
Offline	.11 (.042)	–.03 (.08)	–.10 (.134)	–.06 (.095)	1.65 (.148)	–.04	.17
Strong	.01 (.115)	–.08 (.052)	–.18 (.088)	–.02 (.062)	–.05 (.074)	.88 (.067)	.39
Expert	–.02 (.066)	.07 (.116)	–.08 (.194)	–.13 (.14)	.36 (.163)	.62 (.112)	2.81 (.285)

Table 22: Summary of Hypotheses Results: Seek Information Intentions

Hypothesis	Result	Additional Comments
$H_{1seekinfo}$	Fully supported	
$H_{2seekinfo}$	Fully supported	Positive WOM had a greater absolute effect on seek information intentions than negative WOM. In addition, mixed WOM also had a greater effect on seek information intentions than neutral WOM. The strong correlation of the across-brand random effects for the valence parameters suggest that some brands have much greater information search intentions regardless of WOM valence.
$H_{3seekinfo}$	Fully supported	WOM that occurs in online channels is more likely to motivate additional information search than offline WOM. The large across-brand variance of this estimate implies that this difference may be even greater for certain brands, or nonexistent or reversed for some brands.
$H_{4seekinfo}$	Partially supported	Negative WOM reduces intentions to seek additional information, but this influence is attenuated when the conversation occurs online. Conversely, positive WOM's positive influence on brand information search was not accentuated when the conversation occurred online.
$H_{5seekinfo}$	Fully supported	Strong-tie WOM tends to motivate less overall information search because the positive influence of positive WOM is less when it is between strong ties than weak ties, and the negative influence of negative WOM on information search is even more negative when it is between strong ties.

Discussion: Seek Information Intentions

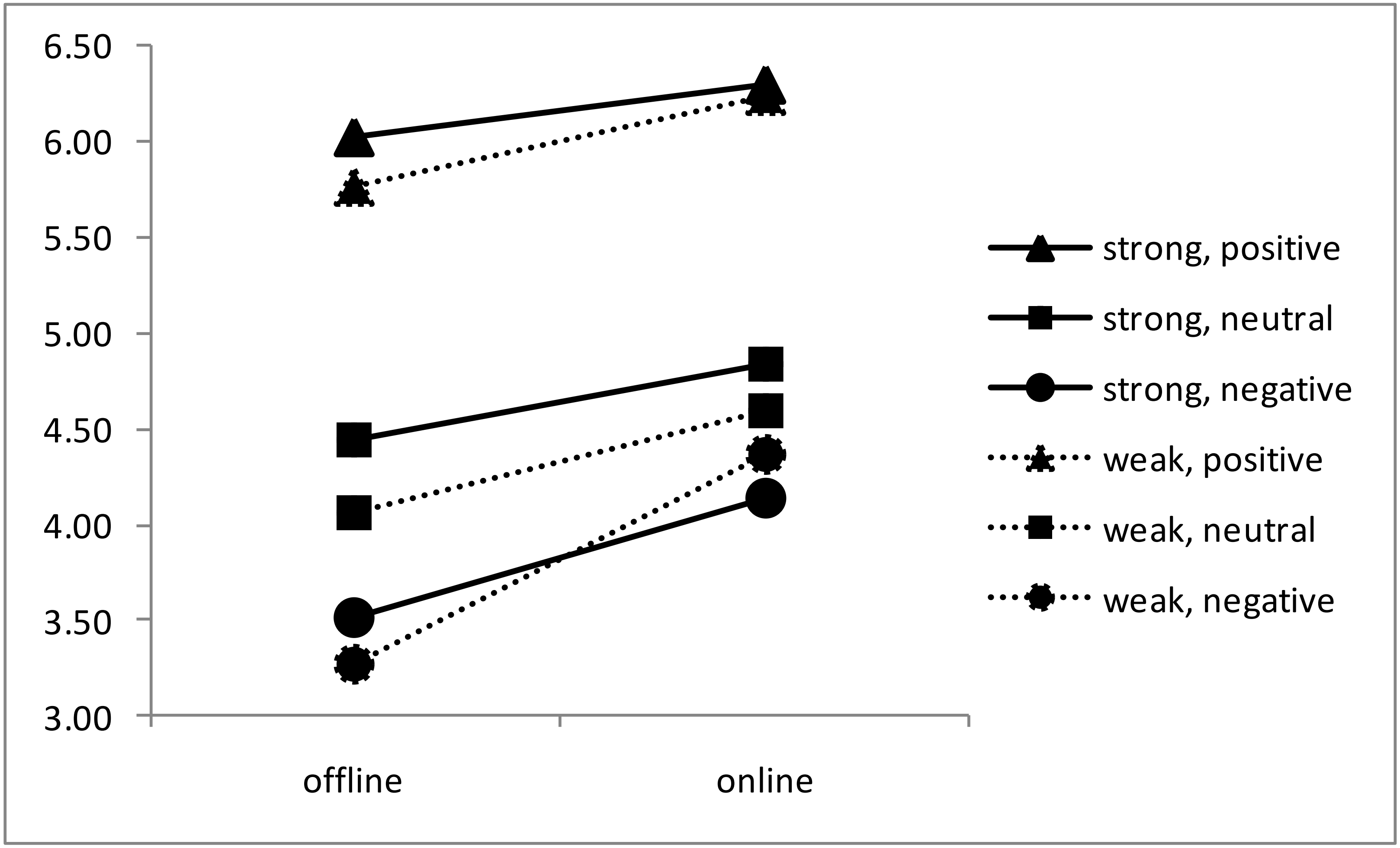
Figure 14 depicts the estimated values of intentions to seek additional information about the brand based on fixed effects only. The raw mean value of the dependent variables when the WOM conversation was online, between weak social ties, and neutral in valence was used as a meaningful intercept (x-hat = 5.3 (.19)).

Positive valence has a positive effect on intentions to seek additional information, and negative sentiment has a negative effect compared with neutral sentiment. Moreover, the data show that positive brand sentiment has a greater absolute effect than negative brand sentiment on intentions to seek additional information. However, unlike intentions to retransmit, WOM conversations occurring online, regardless of valence, have a better chance of inducing the search for additional information. These results suggest that the reduced search costs a consumer has when faced with online brand WOM positively influences intentions to seek additional information. These results are suggestive to brand managers: Positive WOM about a brand tends to create interest and arousal about the brand and additional information search. However, negative WOM does not seem to motivate consumers to seek additional information confirming or disconfirming it. This insight suggests that negative WOM sentiment, even if inaccurate or not representative of the brand as a whole, can be particularly damaging for a brand, as consumers will not go out of their way to assess the veracity of the WOM sentiment.

It is particularly notable that the difference between weak-tie and strong-tie WOM on intentions to seek information about a brand is much more substantial when the conversation occurred offline, while there is essentially no difference between strong and weak ties on intentions to seek additional information when the conversation occurs online. These results

may be interpreted as follows: The reduced search cost of online channels only affect search intentions when the initial brand-related information is coming from a source that is not inherently trusted or well-known (e.g., weak social ties). The reduced search costs of the online channel matter less when a consumer receives information from a source that tends to be trusted (e.g., strong ties).

Figure 14: Predicted Intention to Seek Additional Information Score (Fixed Effects Only)



INVESTIGATION 1 DISCUSSION AND IMPLICATIONS

In this section, I incorporate the findings of the hypothesis testing into the broader academic and practitioner dialogue of how WOM relates to brand performance. First, I discuss considerations for how the results from this investigation support, reshape, and challenge some of the extant contemporary literature on this topic. Next, I present the insights from this investigation with consideration for how they may be used by brand managers. Then, I note some limitations and caveats associated with the current investigation and considerations for further research.

Implications of Marketing Research

According to an extensive review of contemporary marketing literature, this is the first study to empirically compare the impact of offline WOM and online WOM. Researchers have identified this area of inquiry as important. This is particularly significant, given than many of the field's current insights into WOM and marketing performance are based solely on marketing research using only online WOM (Godes and Mayzlin 2004; Godes et al. 2005). The current study demonstrates different consumer-level responses to WOM depending on the channel of WOM occurrence. Offline WOM tends to have a slightly stronger absolute impact on purchase intentions than online WOM. This result suggests that solely examining online WOM may underestimate the positive and detrimental effect of WOM on short-term consequences of brand performance metrics such as sales and market share. Alternatively, to the extent that studies investigating only online WOM may have spuriously associated online WOM impact with performance, online WOM may receive some undue credit in influencing short-term brand performance. Therefore, a recommendation derived from the current results is this: Any study linking WOM to brand performance should attempt to separately estimate online and offline

WOM volumes, because the parameter estimates of their influence are likely to be different. Alternatively, at the least, empirical models of WOM and brand performance should not merely estimate offline WOM to be greater in volume (which Keller [2007] has already been demonstrated), they should also incorporate a some sort of channel force multiplier for the impact of positive and negative WOM in offline channels compared with online channels. This latter option may be more tractable, given the difficulties associated with directly measuring offline WOM. In a broader sense, the insights from this investigation suggest that researchers cannot overlook the importance of the communication channels and the resulting signal/noise ratio fluctuation across channels when linking WOM to consumer outcomes.

This study also contributes to the research dialogue about asymmetric effects of positive and negative information on consumer response. The results from this study are consistent with the multitude of other studies that have shown a general tendency for negative sentiment to have an asymmetrically greater effect on consumer purchase behavior. However, this study also suggests that investigating asymmetric purchase response to WOM may not fully paint the picture of consumer response to WOM activity. Specifically, in terms of motivating additional information search, positive WOM had an asymmetrically greater absolute effect. Thus, while negative WOM dominates in terms of immediate purchase intentions, positive WOM is the dominant factor in motivating the intermediate marketplace behavior of consumer information search. From a brand management perspective, this suggests that positive WOM could ultimately have a equivalent or even dominant net effect on individual consumer purchase if the indirect effect of information search is also incorporated into WOM effect attribution. In addition, when considering how a WOM episode from one consumer may subsequently influence other consumer behavior through retransmission activities, it becomes even less clear

whether negative or positive WOM truly has an asymmetric influence. The results of this study suggest that positive WOM has a much stronger positive influence on retransmission than the positive influence of negative WOM. In other words, both positive and negative brand information tend to trigger retransmission, but positive WOM is stronger. Thus, if the reception of positive WOM tends to trigger more brand advocacy than negative WOM triggers brand detraction, again, the net effect of a positive WOM episode may be larger than negative WOM. In summary, these results provide an intriguing alternative view to the ongoing dialogue about the impact of negative and positive WOM: Incorporating consumer response behaviors beyond mere purchase may dramatically alter the net balance effect of negative and positive information on consumer behavior, at least in the context of WOM. Current marketing research investigating asymmetric influences should incorporate these considerations.

The results of this study also support the "strength of strong ties" notion, albeit with a caveat: Strong ties tend to be more influential in their WOM than weak social ties. However, the results seem somewhat inconsistent with the "strength of strong ties" notion, as this argument prioritizes strong social ties as exceedingly dominant sources of interpersonal influence. The results from the current study seem inconsistent with the intensity of this claim. It is difficult to rectify precisely why this is the case; the operationalization of tie strength varies widely in studies, and the stated social relationship approach used here is a possible explanation for the less intense than anticipated effects. Alternatively, some research has noted that contextual factors can moderate the influence of tie strength (Levin and Cross 2004; Ryu and Feick 2007). The results of this study showed the largest difference between weak and strong social ties on intentions to seek additional information in offline channels. Therefore, a productive avenue for

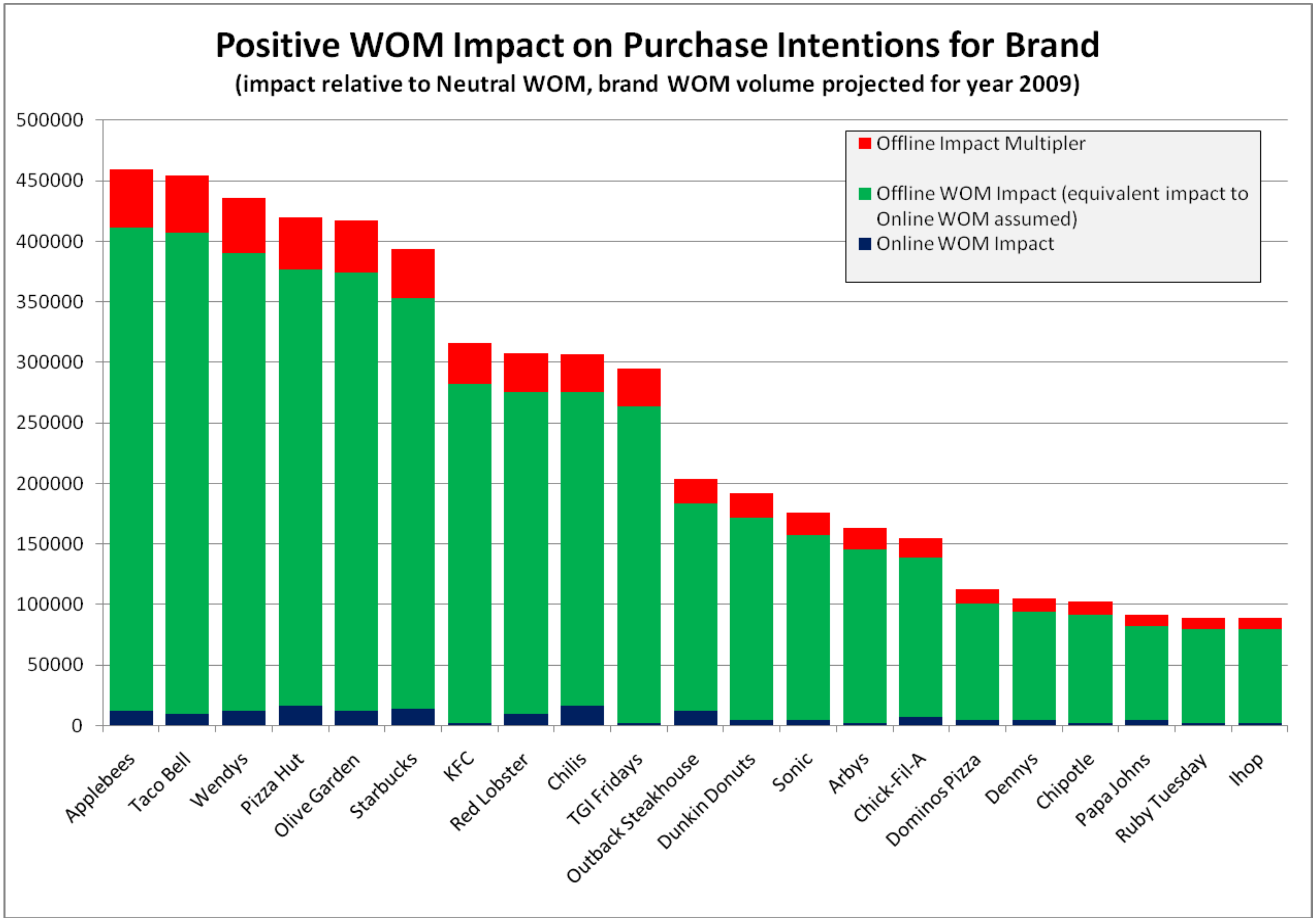
further inquiry would be to investigate whether differences between strong ties and weak ties vary by communication channel characteristics.

Implications for Marketing Management

First, perhaps the most substantial implication of this current study is that marketers endeavoring to measure their brand WOM activity should not simply focus on tracking online WOM given the differential impact of offline and online WOM and volume of offline and online WOM. There are myriad marketing services that track online sentiment. (Radian6, Nielsen BuzzMetrics, and Harris Interactive's Buzz Promoter Score are just a small sampling of these extensive services.) The results of this study suggest that marketers using online WOM as a proxy for all WOM impact are underestimating the influence of WOM. As an illustration of this point, the volume of positive online and positive offline WOM volume for 21 quick service or restaurant chains were projected for the entire year of 2009. This projection was based on 2008 U.S. census estimates of the BrandChat U.S. sample of 13- to 69-year-old respondents as well as a multiplier to project the 12 days of WOM activity captured by BrandChat to the calendar year (see Figure 15). The y-axis illustrates the net impact of WOM under a simplistic scenario that the impact of a positive WOM episode has a positive benefit above neutral WOM +1 arbitrary units. The dark blue shaded area represents the impact of online WOM alone, and the green illustrates the additional impact of offline WOM assuming equivalent impact (+1 arbitrary units) to online positive WOM. The red topmost portion of the bars represents the additional impact of positive WOM if the impact of positive offline WOM is adjusted by the additional impact observed from the empirical results of the first investigation. This adjusted value suggests that a positive WOM conversation would have an impact 1.12 times that of an online positive WOM conversation. This insight is important for marketing managers wanting to justify the additional

expense of tracking offline WOM as well as online WOM—an important point, considering recent research of chief marketing officers suggests WOM is rarely monitored at all and when it is it is, it is usually only in online channels (Alterian 2010; CMO Council 2009).

Figure 15: Illustrating Impact of Positive WOM With and Without Offline Channel Multiplier

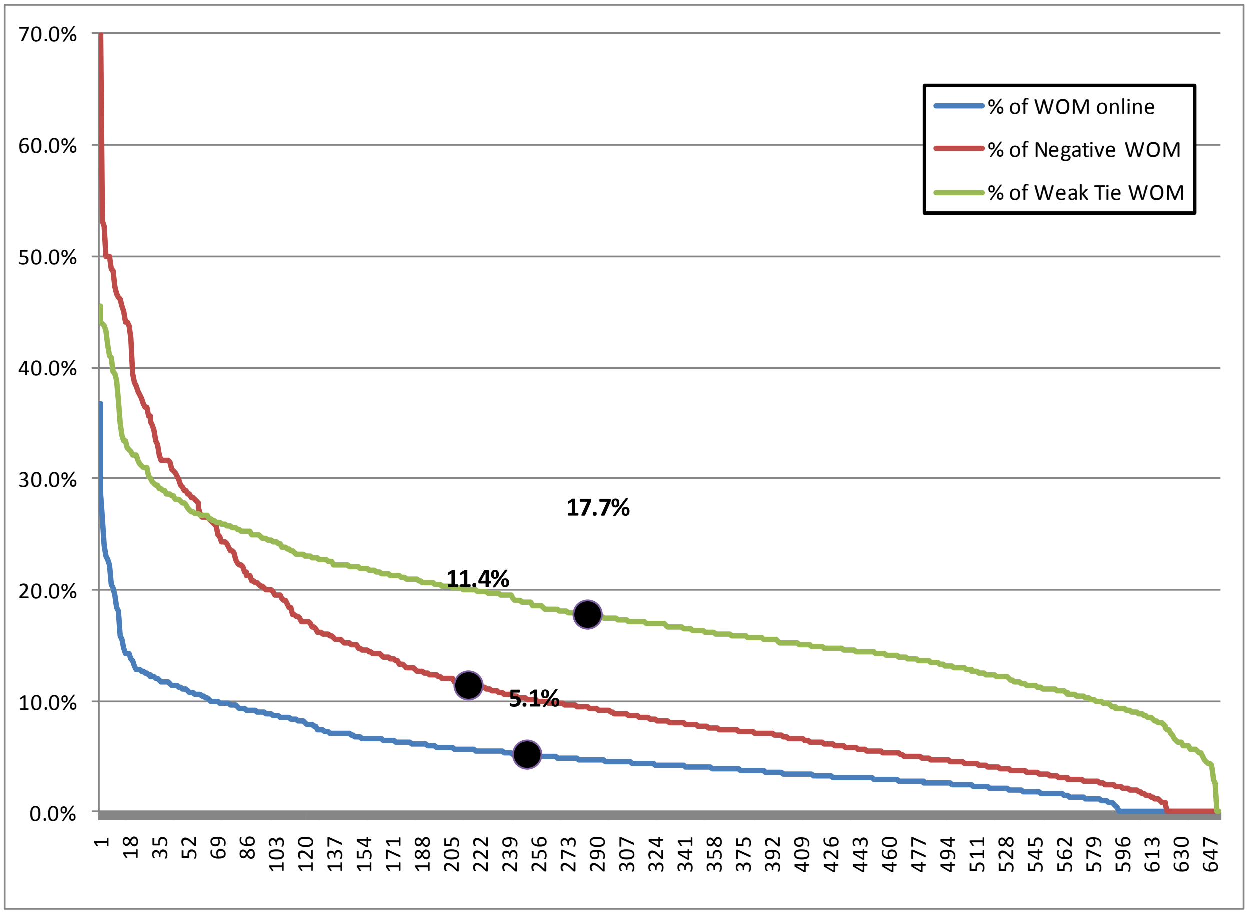


Second, the results of this study indicate that people with close social relationships do tend to have greater positive influence on WOM recipients. Recent research into referral rewards programs have indicated that different monetary incentive structures (whether only one party of both parties receive a product discount; Ryu and Feick 2007) are more effective depending on the social tie strength. Ryu and Feick (2007) suggest that referral rewards in which both parties enjoy a benefit were best between strong social ties. the results from the current research suggest that given the higher frequency and increased impact of strong-tie WOM, marketers should design referral rewards programs that benefit both parties rather than just the referrer. Conversely, the differences between weak and strong social ties on motivating purchase were not as substantial as has been signaled by marketing practitioner research about consumer self-reported sources of interpersonal influence (Mcilroy 2008; Nielsen Consumer Research 2009). Thus, a different interpretation of these results would suggest that marketers currently fixated with WOM between close interpersonal relationships may be unduly focused on only one form of impactful WOM. For example, consider that the wording of NPS focuses explicitly on measuring WOM advocacy with relatively stronger social ties. This measurement approach may be a mistake, especially for brands that have a disproportionately higher share of weak-tie WOM. Figure 15 illustrates that of the brands sampled in this investigation, the average amount of weak-tie WOM was 17.7%. However, 14.2% of the brands sampled had more than 25% of their total WOM between weak ties.

Third, the results of this study also have implications for marketers engaging in viral or buzz marketing activities—marketing efforts designed to induce socially contagious WOM about a brand or product. Viral and buzz marketers have focused exclusively on online channels on the

basis of the presumption that the speed and ease of WOM transmission in online channels facilitates the social contagion process (Kozinets et al. 2010). However, the results of this study suggest that the potency of offline channels positively moderates the effect of WOM retransmission. As such, it would be beneficial for such marketers to engage in tactics that blend both online and offline activities. Event marketing may a particularly salient way to cultivate offline WOM about brands. It is notable that the current study did not differentiate where the catalyst for the WOM conversation occurred (e.g., a bad online experience with a brand can certainly be discussed at a later time offline). As such, the question remains whether brand experiences in offline or online channels tend to produce a greater amount of same-channel WOM.

Figure 16: Ratio of WOM by Social Tie, Valence, and Channel Across Sampled Brands



Average percentage noted by black dots across the three lines.

Limitations and Future Directions

It has been argued that the BrandChat databases provide a rich and extensive WOM sample that has numerous advantageous qualities over many contemporary marketing studies investigating WOM. However, this does not mean that the BrandChat WOM measures are flawless; the implications of some limitations are considered next. First, BrandChat measures of WOM activity almost certainly are not a perfect representation of all WOM activity about brands in the marketplace. The BrandChat measures recalled WOM conversations in the previous 24 hours with the aid of a guided survey instrument. First, because BrandChat relies on respondent recollection, it is reasonable to speculate that WOM conversations occurring when the BrandChat respondent had low motivation, ability, or opportunity to encode the message are underrepresented. Although such conversations likely have less overall potent influence on marketplace behaviors, it would be an overstatement to say that occurred-but-unrecalled WOM episodes are irrelevant in driving marketplace behavior. A controlled laboratory study would be a much more fruitful method to investigate how such WOM activity may shape behavior. It may be speculated that this form of WOM may act similarly to incidental brand exposures (Ferraro et al. 2009). In addition, BrandChat respondents may be hesitant to share information about conversations for some brands. For example, some brands may carry some social stigma (e.g., contraceptives, tobacco, liquor; Smith 2000).

Another limitation of the BrandChat database is that the data extraction mechanism was somewhat limited in its sophistication. Specifically, only a certain amount of detail about the WOM conversations could be simultaneously extracted for the models. Thus, at present, analyzing WOM outcomes for differences across respondent characteristics (e.g., men vs.

women,) could not be performed. Although this is not a limitation of the current study per se, as such differences were not in its scope, differences in WOM impact across different consumer groups are of interest to marketers. Further research is already under way to delve further into such group differences.

Given that the current investigation measures BrandChat responses to WOM as intentions and not actual behavior, the known problems of treating consumer-stated intentions as literal determinants of actual future behavior must be noted as well (Manski 1990). A review of the literature shows consensus that, broadly speaking, increased (decreased) stated intentions are associated with increases (decreases) in actual purchase behavior; however, the best-fitting mathematical relationship between intentions and behaviors is conditional on characteristics of the brand, product, and the specific presentation of the intentions questions, among other factors (Kalwani and Silk 1982). The current investigation's focus is to provide relative impact of WOM forms on behaviors; as such, interpretation of intentions responses should serve this goal well. However, extending the current investigation's results to provide specific, brand-level aggregate predictions of brand sales and WOM volume as a result of different forms of WOM activity would be a valuable research question extending other marketing research efforts that have sought to establish tenable empirical models between consumer-stated intentions and behavior (Morwitz and Schmittlein 1992; Morwitz et al. 2007). An added additional challenge in the specific case of BrandChat is that some of the stated intention responses are actually statements of actual behavior. Modeling the latent heterogeneity in the high-end responses for such lagged-response questions would be another fruitful methodological study.

As with any type of single-respondent survey study, the independent and dependent variables examined here are collected from the same respondent. Thus, validity threats

attributable to common methods variance (CMV) are potential confounds to the empirical insights. In this case, CMV threats are likely minimal; for example, it is difficult to theorize how a respondent's statement of the WOM channel and fellow WOM participant would induce systematic covariance with the dependent variables. Unfortunately, no known method explicitly and empirically tests for the CMV threat, so this remains a potential limitation of the current study.

CHAPTER 4: INVESTIGATION 2: DOES THE IMPACT OF WOM CONVERSATIONS VARY ACROSS BRANDS AND CATEGORIES?

The previous analysis sought to explain the general impact of consumer WOM and how message, interpersonal, and communication channel characteristics affected immediate consumer brand purchase, message retransmission, and additional brand information search behaviors. Although this analysis accounted for the possibility of variance in effects of WOM characteristics across brands (allowing the intercept and main effects investigated to vary randomly across brands), the variance of WOM impact across brands was ultimately treated as background noise. This approach was sound insofar as Investigation 1's goal was to focus specifically on conversation-specific mechanisms; however, brand-specific characteristics and the general category in which a brand competes are likely meaningful factors that may uniquely influence how WOM affects consumer response. Identifying theoretically relevant and managerially salient brand characteristics that shape consumer-level response to WOM would be valuable, as it can provide insight into conditions in which WOM is more or less impactful on individual-level response. Establishing links between WOM and market-based assets such as brand equity and customer equity (enduring satisfaction) are important because market-based assets are theoretically (Srivastava et al. 1998) and empirically linked (Morgan and Rego 2006; Srivastava 2009) to firm performance, and WOM can be directly and indirectly influenced by marketers. Brand equity is a particularly important concept that serves as a meaningful bridge between the long-term strategic efforts of marketing managers and the investment community, and there are strong indications that brand value is considered in investors' stock evaluations (Barth et al. 1998) and that strong brands result in stock returns that beat benchmarks and do so

with less risk (Madden et al. 2006). Furthermore, although WOM has long been recognized as a process by which these market-based assets lead to positive benefits for the firm (Keller and Lehmann 2006; Rust et al. 2004a), no known empirical research has investigated how such market-based assets modify the influence of individual WOM episodes.

In this analysis, I analyze a subset of the original brands investigated and introduce covariates for the product category in which the brand competes and the overall strength of the brand, indicated by the average American Consumer Satisfaction Index (ACSI) and Equitrend Brand Equity value for the brand over the course of the WOM observational period. These two indicators determine brand health in related but distinct ways. First, the ACSI serves as a general indicator of extant customer satisfaction toward the overall brand; as such, it is a broad indicator of the extent to which a brand is able to meet and exceed the expectations of customers. The Equitrend Brand Equity index value represents general consumer sentiment toward a brand on a composite of brand familiarity, perceived quality, and purchase consideration. As such, this brand equity indicator represents a consumer-wide (beyond extant customers) indicator of a brand's relative strength to be perceived distinctly and positively among other national brands.

Hypotheses for Investigation 2: The Role of Overall Brand Satisfaction

Researchers have speculated that the link between customer satisfaction and marketing performance metrics is partly the result of free WOM advocacy created by satisfied customers. This interpretation has been suggested as an explanatory mechanism for why high levels of company-level satisfaction are strongly associated with greater advertising efficiencies in future periods (Luo and Homburg 2007). This perspective is consistent with many consumer-level studies that demonstrate that satisfaction is linked with advocacy (Anderson 1998). In addition,

low levels of satisfaction may be disproportionately influential in generating negative WOM, suggesting that dissatisfaction will have an even greater influence on generating negative WOM. An online review of business press, marketing conference reports, and marketing blogs revealed hundreds of examples of the sentiment "a happy customer tells [some number] of people; an unhappy customer tells [some number large multiplier]" being discussed as though it is a nearly universal empirical regularity (Blackshaw 2008). This perspective explicitly suggests that dissatisfaction breeds negative WOM faster than satisfaction generates positive WOM. However, these explanations of how overall customer satisfaction affects WOM address the volume of WOM generation, not the strength of the effect of a WOM conversation.

Another mechanism by which customer satisfaction may influence WOM impact is through moderating the impact of, or consumer-level response to, individual WOM episodes. From this perspective, brands with enduring positive customer satisfaction may have more consumer-level impact for each positive WOM episode because the individual episode is consistent with background marketplace signals about the brand. In other words, overall brand-level customer satisfaction is already lurking, albeit passively, in the back of the mind of the WOM recipient, and the positively received episode is particularly impactful because it acts as both a positive influence and a catalyst by making salient the current positive marketplace beliefs about the brand. Conversely, a negative WOM episode received about a brand that is generally considered favorably in the marketplace may be less impactful because it is inconsistent with the background environment.

H_1: Compared with brands with lower levels of overall customer satisfaction, brands with higher levels of overall customer satisfaction have (a) higher levels of intentions to purchase the brand when a consumer receives positive WOM about the brand and (b) higher levels of intentions to purchase the brand even when a consumer receives negative WOM about the brand.

Another advantage brands with overall marketplace satisfaction may benefit from is how an individual WOM episode motivates the WOM recipient to retransmit the brand-related information. Positive messages received about a brand with high levels of satisfaction may be more likely to be passed along, because its consistency with enduring marketplace beliefs means there is relatively little social risk in passing along the information (Sundaram et al. 1998; Westbrook 1987), while received negative information about a brand may be less likely to be passed along than received negative information about brands with lower levels of enduring marketplace satisfaction. It is important to consider that because the WOM recipient did not personally experience the brand episode that induced the positive and negative valence, this issue of social risk associated with retransmission should be salient.

> **H_2:** Compared with brands with lower levels of overall customer satisfaction, brands with higher levels of overall customer satisfaction have (a) higher levels of intentions to retransmit WOM when a consumer receives positive WOM about the brand and (b) lower levels of intentions to retransmit WOM when a consumer receives negative WOM about the brand.

Finally, brands with higher levels of enduring customer satisfaction may motivate WOM recipients differently in terms of causing the WOM recipient to seek additional information about the brand. For brands with positive levels of enduring satisfaction, the reception of positive WOM may motivate arousal about the brand and particularly influence additional search: Consumers will be more inclined to seek confirmation or additional information for positive information about a brand known to create general customer satisfaction. Conversely, negative WOM may also motivate additional search, because the information is contrary to the background marketplace sentiment, and thus be motivation for additional inquiry into the veracity of the sentiment (Friestad and Wright 1994). A similar mechanism operating here is that

people tend to be intrigued when prominent/popular figures fall into scandal (a "watching the mighty fall" effect). However, for brands with lower levels of overall satisfaction, a WOM recipient of positive news may still discount any positive information and thus be less likely to seek more information, while negative WOM may further inhibit the search for additional information.

> **H_3:** Compared with brands with lower levels of overall customer satisfaction, brands with higher levels of overall customer satisfaction have (a) higher levels of intentions to seek additional information when a consumer receives positive WOM about the brand and (b) higher levels of intentions to seek additional information when a consumer receives negative WOM about the brand.

Hypotheses for Investigation 2: The Role of Overall Brand Equity

Brands with characteristically high levels of brand equity are expected to be relatively more well-known and have more overall positive associations about them (Keller 2001). Brands that are well-known and have enduringly positive mental associations likely benefit from greater WOM impact on purchase intentions partly by virtue of being a recognized brand. (There is already awareness about the brand, so the WOM episode is building on an existing knowledge structure.) Moreover, strong brands already have positive mental associations in a consumer's mind, so any WOM episode, regardless of the valence of the brand sentiment, may motivate purchase of the brand. From this perspective, brands with strong overall brand equity should have higher purchase intentions resulting from a WOM episode regardless of the WOM sentiment. Conversely, brands with negative brand equity likely do not reap as great a benefit from a positively valenced WOM episode, and negative sentiment only further reinforces existing negative knowledge structures and diminishes likelihood of purchase.

> **H_4:** Compared with brands with lower levels of overall brand equity, brands with higher levels of overall brand equity have (a) higher levels of intentions to purchase the

brand when a consumer receives positive WOM about the brand and (b) higher levels of intentions to purchase the brand even when a consumer receives negative WOM about the brand.

When brands are generally well-known and perceived positively, they should also be resistant to having negative sentiment about them passed along by someone who only heard the WOM but did not experience it. Conversely, passing along the good news about a brand with high levels of brand equity is more likely because the recipient of the initial message transmission is familiar with the brand and can anticipate that a future audience is familiar with the brand. Brands with low levels of equity, however, tend to be less known in the first place (and less positively received when they are known), implying that there will be greater social risk associated with passing along positive sentiment about a less-known or less-liked brand. However, negative sentiment received about a brand with low equity would be passing along information that is consistent with general consumer sentiment. Thus, there may be less of a difference in retransmission tendencies for negative WOM received about brands with either higher or lower brand equity. This notion is consistent with perspectives of the circumstances that facilitate different types of rumor spreading: Positive news about liked others (in this case, generally well-known and liked brands) is a source of status enhancement, whereas negative news about disliked, outside others (in this case, less-known and generally less-liked brands) is a stronger form of status enhancement (McAndrew and Milenkovic 2002).

H_5: Compared with brands with lower levels of overall brand equity, brands with higher levels of overall brand equity have (a) higher levels of intentions to retransmit WOM when a consumer receives positive WOM about the brand and (b) lower levels of intentions to retransmit WOM when a consumer receives negative WOM about the brand.

When a WOM recipient receives negative sentiment about a well-known and generally liked brand, there should be a greater motivation to seek additional information about the brand to seek confirmation or disconfirmation of the brand sentiment. Conversely, for less-known and less liked (low brand equity) brands, negative sentiment should be unsuccessful at motivating any additional information search. However, hearing positive sentiment about a less-known or less-liked brand may stimulate a WOM recipient to seek additional information about a brand. Thus, while receiving positive news about a brand may be successful in motivating information search for brands with high and low brand equity, negative WOM recipients should seek additional information for brands with high levels of equity more than for brands with low brand equity.

> **H_6:** Compared with brands with lower levels of overall brand equity, brands with higher levels of overall brand equity have higher levels of intentions to seek additional information when a consumer receives negative WOM about the brand.

Furthermore, for brands with high levels of brand equity, it should be less important how a WOM recipient perceives the transmitter of the WOM sentiment, at least in terms of motivating additional information search about the brand. If the brand itself is known and generally well liked (higher brand equity), WOM received from strangers or acquaintances about the brand (weak tie) may be just as influential at motivating additional information search as if it were received from a closely known person (strong tie). This effect may persist as the brand itself is already known with a generally positive association, and thus less importance is placed on the credibility of the message source. Conversely, less-known and less-liked brands (low brand equity) likely are not as impactful at motivating additional information search when the WOM episode also occurs between relatively less-known persons (weak ties). This rationale may

also be applied to motivating actual purchase as well, but given the much larger cost and effort associated with purchase than merely seeking out additional information about a brand, it may be that weak social ties are still less influential at influencing purchase behaviors. In short, source credibility is known to be an important influencer of behavior (Chaiken 1980); therefore, typically, weak ties would be expected to drive less WOM recipient behavior. However, if the brand itself is generally credible then weak ties WOM should have similar levels of effectiveness relative to strong tie WOM interactions.

> **H_7:** Compared with brands with lower levels of overall brand equity, brands with higher levels of overall brand equity have (a) greater levels of intentions to purchase the brand when a consumer receives WOM from a weak social tie and (b) higher levels of intentions to seek additional information when a consumer receives WOM from a weak social tie.

Hypotheses for Investigation 2: Product Category Characteristics

The total impact of WOM on consumer behavior is likely to be partly contingent on properties of the product or service category primarily associated with the brand. For example, previous research has shown WOM be more impactful when the product is an experiential good (service), because without the ability to easily assess quality/performance before purchase, the experiences of others can be a valuable information source (Neelamegham and Jain 1999). Moreover, many studies of online movie reviews have speculated that the reason WOM is so effective in that context is because movie tickets are relatively cheap, they often are somewhat spontaneous purchases, and movie consumption poses little long-term downside for a consumer (Liu 2006). In such instances, even bad reviews may influence purchase because it may increase awareness and interest. Likewise, restaurants have been suggested to be particularly reliant on WOM given their relatively low-risk consumption experiences. On the other In contrast, an

individual WOM episode is less likely to motivate purchase in categories high-cost or long–ownership duration products because a variety of sources are likely to be used in such complex purchasing scenarios (Sultan et al. 1990). Likewise, some product and service categories have high notable switching barriers (e.g., health insurance) making it difficult or impossible for a consumer to immediately act on a WOM message (Duhan et al. 1997). This does not mean that WOM does not play an important role in the decision process; rather, an individual WOM episode may not have the same immediate impact in these categories given that either the consumer engages in greater total search or it is difficult for the consumer to act on the WOM because he or she is unable to easily switch out of a current service or product being used. On the basis of these considerations, different product categories are likely to have substantially different overall levels of purchase intentions resulting from a single WOM episode. However, there are likely fewer differences between product categories in terms of WOM retransmission or seeking out additional information about a brand because these two responses have equivalent risks and costs for a consumer regardless of the actual properties of the brand's product category.

> **H_8:** The product category of a brand influences a WOM recipient's tendency to purchase a brand as a result of the WOM episode. Differences will be less substantial between product categories for a WOM recipient to retransmit a message or seek additional information.

Table 23 and Figure 17 present the hypotheses and the research model, respectively. Next, I discuss the empirical model, the new data used for analysis, and results of the hypothesis tests.

Figure 17: Research Model and Hypotheses for Analysis of Brand-Level Variables Influencing WOM Conversation Outcomes

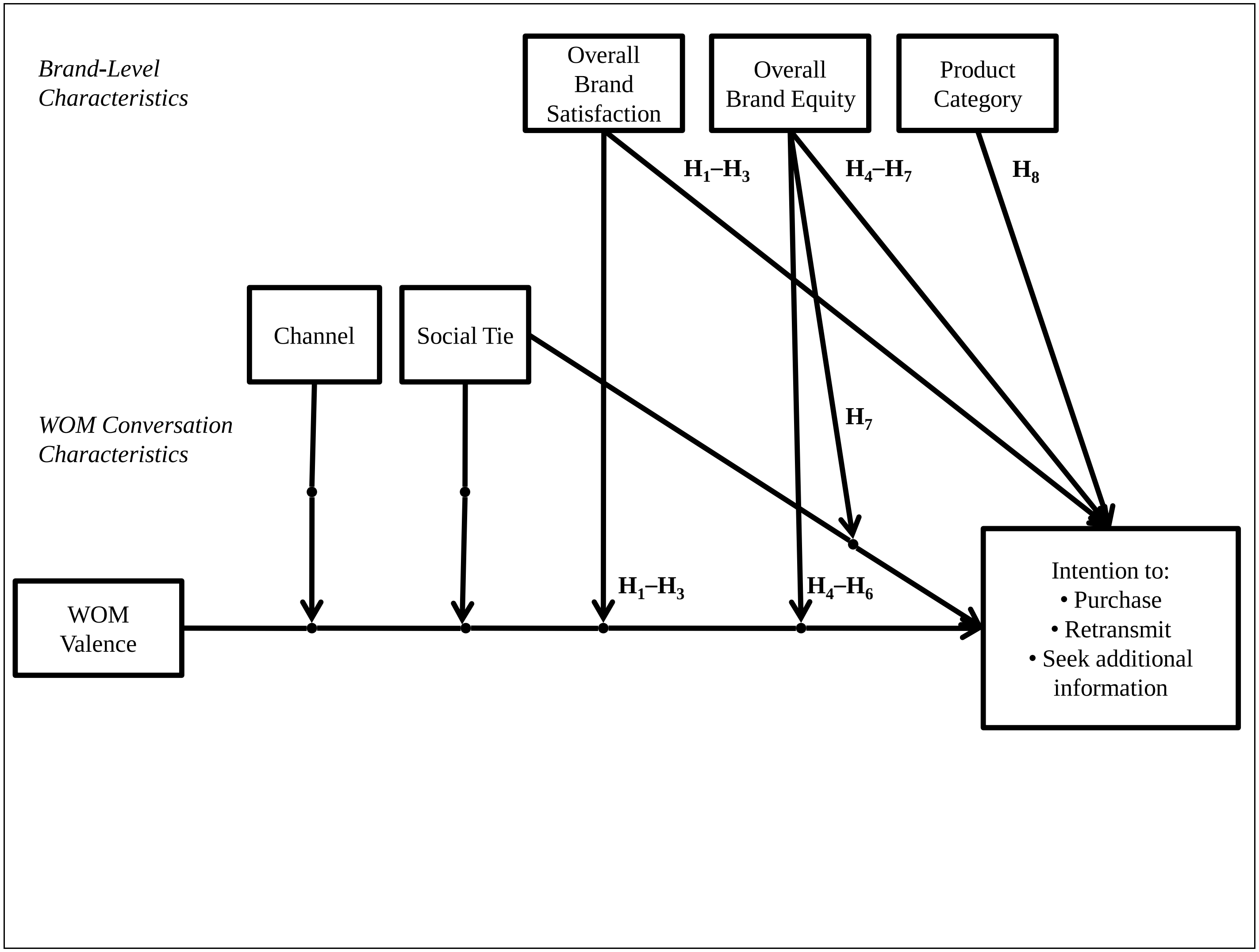


Table 23: Hypotheses Summary for Analysis of Brand-Level Variables Influencing WOM Conversation Outcomes

Characteristic	Hypothesis	Reasoning	Supporting Literature
Brand Satisfaction × Valence	**H_1:** Compared with brands with lower levels of overall customer satisfaction, brands with higher levels of overall customer satisfaction have (a) higher levels of intentions to purchase the brand when a consumer receives positive WOM about the brand and (b) higher levels of intentions to purchase the brand even when a consumer receives negative WOM about the brand.	Enduring positive marketplace customer sentiment will tend to act as an accentuating background context for individual WOM episodes.	(Keller and Lehmann 2006)
Brand Satisfaction × Valence	**H_2:** Compared with brands with lower levels of overall customer satisfaction, brands with higher levels of overall customer satisfaction have (a) higher levels of intentions to retransmit WOM when a consumer receives positive WOM about the brand and (b) lower levels of intentions to retransmit WOM when a consumer receives negative WOM about the brand.	High satisfaction brands will tend to enjoy less social risk associated with transmitting positive WOM and greater social risk with resending negative WOM.	(Sundaram et al. 1998; Westbrook 1987)
Brand Satisfaction × Valence	**H_3:** Compared with brands with lower levels of overall customer satisfaction, brands with higher levels of overall customer satisfaction have (a) higher levels of intentions to seek additional information when a consumer receives positive WOM about the brand and (b) higher levels of intentions to seek additional information when a consumer receives negative WOM about the brand.	Generally high-satisfaction brands will serve to amplify the arousal to seek information after receiving good news for a brand, while negative news will also motivate additional search but because there is intrigue to confirm/challenge the bad news ("watching the mighty fall").	(Friestad and Wright 1994)
Brand Equity × Valence	**H_4:** Compared with brands with lower levels of overall brand equity, brands with higher levels of overall brand equity have (a) higher levels of intentions to purchase the brand when a consumer receives positive WOM about the brand and (b) higher levels of intentions to purchase the brand even when a consumer receives negative WOM about the brand..	Strong brands will have more impactful positive WOM because the single episode is merely building on the preexisting awareness/positive associations of the brand.	(Keller 2001)
Brand Equity × Valence	**H_5:** Compared to brands with lower levels of overall brand equity, brands with higher levels of overall brand equity will tend to have: (a) higher levels of intentions to retransmit WOM when a consumer receives positive WOM about the brand. (b) lower levels of intentions to retransmit WOM when a consumer receives negative WOM about the brand.	Brands with high overall equity will have positive WOM generally judged to be a valuable form of status enhancement and thus retransmitted, while negative WOM will be retransmitted for weak brands because consistent negative WOM is a way to build social capital among the "unallied" brand.	(McAndrew and Milenkovic 2002)
Brand Equity × Valence	**H_6:** Compared with brands with lower levels of overall brand equity, brands with higher levels of overall brand equity have higher levels of intentions to seek additional information when a consumer receives negative WOM about the brand.	Attraction to strong brands will motivate even more search when receiving positive news, while negative WOM will motivate intrigue or skepticism about a strong brand and will also have higher levels of information search.	(Friestad and Wright 1994)
Brand Equity × Social Tie	**H_7:** Compared with brands with lower levels of overall brand equity, brands with higher levels of overall brand equity have (a) greater levels of intentions to purchase the brand when a consumer receives WOM from a weak social tie and (b) higher levels of intentions to seek additional information when a consumer receives WOM from a weak social tie.	Strong brands are themselves a credible source; thus, WOM received from relatively less known and less credible weak ties should still influence WOM recipient behavior.	(Chaiken 1980)
Product Category	**H_8:** The product category of a brand influences a WOM recipient's tendency to purchase a brand as a result of the WOM episode. Differences will be less substantial between product categories for a WOM recipient to retransmit a message or seek additional information.		

DATA AND METHOD: INVESTIGATION 2

Databases Used for Analysis

The BrandChat database was again used to provide the WOM conversations about brands for the second analysis. The operationalization of all variables in the BrandChat database remains the same as Investigation 1. The new databases and variables used uniquely for Investigation 2 are discussed in the following section.

American Consumer Satisfaction Index

The ACSI is the secondary data source used to represent a brand-level aggregate of customer satisfaction for a brand. The ACSI's coverage is extensive, including 10 economic sectors (e.g., e-commerce, accommodation & food services, retail trade) and more than 200 firms (the exact number varies depending on the particular year). The aggregate ACSI score is commonly used as a leading economic indicator, and firm-level ACSI scores have been used in a variety of marketing research to predict such things as supranormal returns in financial portfolios (Aksoy et al. 2008) and the efficiency of future advertising investments (Luo and Homburg 2007), among other financial outcomes (for more examples, see Anderson et al. 2004; Fornell et al. 2006; Gruca and Rego 2005; Mithas et al. 2005). The results for particular economic sectors are reported once a year during a specific quarter.

Given the ACSI's focus as an economic indicator, firms represented there are not a fair representation of all firms in a particular economic sector: ACSI coverage is biased toward large, publicly traded firms. This is a limitation for the current study, as this means that many brands regularly discussed by consumers and represented in the BrandChat database may not have a

corresponding firm with an ACSI score because the brand is part of a privately held company, the firm is a relatively small player in the market, or the economic sector the brand's firm competes in is not covered by ACSI. The ACSI Corporate Research Program and Proprietary Research Program make it possible that additional firms or brand-level ACSI scores are derived, but these data are not made publicly available.

More than 65,000 consumers are interviewed annually for the ACSI, and on average, 200 recent customers of a firm are used to derive the satisfaction index value (possible range 0–100, 100 being the best possible score) for a particular firm. Computer-assisted telephone interviews are used to collect most data, though online panels are used to collect data about e-companies. All respondents are screened to ensure that their consumption experience with products and brands is representative of the particular economic sector under study by the ACSI at a particular time (i.e., the respondent must have been a customer). The ACSI uses 15 questions (all asked on a 10-point scale) to estimate the six latent constructs in the ACSI model (antecedents to satisfaction = [1] customer expectations, [2] perceived quality, and [3] perceived value; [4] satisfaction; consequences of satisfaction = [5] customer complaints and [6] customer loyalty). Next, ACSI analysts use partial least squares to estimate the model and derive estimated weights for the three satisfaction-specific questions that maximize the prediction of customer loyalty. The customer satisfaction–derived weights are adjusted into a 0- to 100-point index, which is the ACSI value reported publicly. Because consumer respondents to the ACSI system generally reference a particular brand when answering their satisfaction-related questions, the ACSI aggregates these results to the level of the firm (for additional details about the ACSI procedures, see Fornell et al. 1996).

Given the ACSI's focus as a financial indicator, it follows that consumer-level satisfaction is expressed at the brand level but is aggregated for ACSI to the overall level of the firm. However, for the current study, the interest is in how overall enduring brand-level satisfaction may affect how individual WOM episodes influence consumer response. Thus, it is necessary to carefully consider how to merge the brand-level WOM responses with firm-level ACSI responses. To do this, a few points were taken into consideration. First, in some circumstances, the firm name is explicitly tied to essentially all consumer-level brand names (e.g., Apple Computer, Best Buy, Starbucks), and thus, such ACSI scores were matched with WOM conversations referencing such brands (e.g., conversations about Diet Coke were linked to Coca-Cola). In other instances, a firm has some offerings for which consumer-level brand names are not always connected to the firm name, though many are (e.g., Coca-Cola and HP). In these instances, WOM conversations specifically referencing a brand name that matches the firm-level name were matched together, but nonexplicit matches were not linked (e.g., WOM conversations about Gatorade were not linked to the ACSI score for PepsiCo). Some publicly reported ACSI scores were not necessarily at the firm level (e.g., Dodge is in ACSI, though Chrysler Group LLC is the ultimate firm). As a result of this criteria, 145 ACSI values were retained from 2007, 146 for both 2008 and 2009, and 150 brands for 2010. Table 24 reports descriptive characteristics of the ACSI scores across years. In addition, the table lists the full ACSI sample for 2007, 2008, and 2009 to verify that the BrandChat-linked sample was consistent with the entire population of ACSI scores for a given year. Aside from a slightly larger standard deviation for the smaller BrandChat-linked sample, the distribution between the full ACSI scores and the linked sample is descriptively similar.

Customer Satisfaction Measure

The mean annual ACSI score for a brand was used as the overall indicator of the general customer satisfaction level customers have for a brand (x-bar = 76.6,σ = 7.4).

Table 24: Descriptive Statistics of ACSI Values Linked to BrandChat Database

	ACSI2007	ACSI2007 (full ACSI)	ACSI2008	ACSI 2008 (full ACSI)	ACSI2009	ACSI 2009 (full ACSI)	ACSI2010
M	76.2	76.03	76.3	76.2	77.2	76.8	77.5
Median	77.0	76	77.00	76	78.0	77	78.0
SD	7.1	6.7	7.4	6.7	7.4	6.7	6.3
Skewness	–.71	–.62	–.89	–.73	–.82	–.63	–.86
Kurtosis	.29	.34	.82	.95	.87	.87	.60
Min.	55	55	54	54	51	51	60
Max.	90	90	89	89	89	89	89
10th percentile	66	67	68	69	68	69	68
90th percentile	84	84	85	85	86	86	85
N	145	215	146	217	146	215	150

Full-sample ACSI comparisons do not reflect descriptions of scores from raw ACSI report because some government services firms were irrelevant to present analysis or had to be recoded to reflect mean of several scores for the same firm (e.g., AT&T).Full 2010 ACSI is not reported because similarity between three years of ACSI results indicated it was only necessary to collect BrandChat-related ACSI scores for 2010.

Harris Interactive Brand Equity

The 2006, 2007, and 2008 *BrandWeek Superbrands* annual special reports were used to compile brand equity measures. The brand equity measures provided in these reports are a subset of the more than 1200 brands measured by the annual Harris Interactive EquiTrend study. According to Harris Interactive, the EquiTrend study is an online survey using a nationally representative sample (weighted to by representative of age, sex, education, race/ethnicity, region and income) of U.S. consumers aged 15 years and older. More than 20,000 consumers respond to the annual survey, with each respondent rating 60 randomly selected brands. On average, each brand receives 1,000 evaluations.

The EquiTrend brand equity measure for brands is derived from three questions. First, familiarity of the brand is measured on a 5-point scale (1 = *never heard of brand,* 2 = *just know the brand,* 3 = *somewhat familiar with brand*, 4 = *very familiar with brand*, and 5 = *extremely familiar with brand*). which is averaged and rescaled to reflect a possible range from 0 to 1. Second, perceived quality is measured on an 11-point scale (0 = *unacceptable/poor*, 5 = *quite acceptable,* 10 = *outstanding/extraordinary*), including the option to have no opinion about the brand's quality. Third, purchase consideration was measured on a 4-point scale (1 = *never*, 2 = *not likely*, 3 = *possibly,* and 4 = *absolutely*). These scores were subsequently rescaled to reflect the 0–10 metric of perceived brand quality. Perceived quality and purchase consideration were indexed and averaged together, and this value was then multiplied by a weighted familiarity score to derive the brand equity score (range 0–100) (*BrandWeek* 2008; *BrandWeek* 2009)

The brand equity measures were captured from the *Superbrands* reports because the full Equitrend database was not accessible. However, this resulted in a smaller subset of brands with

brand equity scores to use for analysis. In addition, the brands with brand equity scores were biased toward characteristics of the brands populating the *Superbrands* reports. The *Superbrands* reports provide detailed brand equity information for the top brands in each product category in their report. The 2006 report had 26 distinct product categories with a category minimum of 4 and maximum of 52 brands. In total, 366 brands had brand equity scores. The 2007 report had 26 distinct categories and 360 brands with brand equity scores, and the 2008 report had 23 categories and 315 brands with brand equity scores. Table 26 illustrates the number of brands with brand equity scores represented by the various *Superbrands* categories and the report year. The brands in the *Superbrands* detailed category reports are there by virtue of being top annual performers in their respective product category (usually ranked by sales in dollars) and being in the Harris Interactive Equitrend pool of brands. As such, brands with brand equity measures are likely biased toward larger brands with greater market share and are limited to the categories represented in the *Superbrands* reports.

One of the advantages of using the Equitrend brand equity measures for the present analysis is that they are truly brand-level measures of brand equity, rather than firm-level estimates of brand equity (e.g., financial measures of brand equity such as Interbrand 2008 and Millward Brown's BrandZ financial estimates 2009). As such, linking the Equitrend brand equity measures to BrandChat brands was more straightforward than the ACSI case. After verifying that the Equitrend and BrandChat brand names were written equivalently, the brands were given a shared numerical identification and linked in the database. Given that the BrandChat database only had complete years of WOM data beginning 2007, only the 2007 and 2008 *Equitrend* scored were used for any analyses. Of the brands in the 2007 *Superbrands* report, 205 (56.7%) were matched with the BrandChat database, and 196 (62.2%) of the brands

from the 2008 report were matched. Table 25 reports descriptive statistics of the brand equity values for 2007 and 2008.

Note that this is not the only way to measure brand equity. For example, Sriram, Balachander, and Kalwani (2007) estimate brand equity not using survey-based data directly but instead inferring brand equity through the modeling of store-level scanner data for toothpaste and dish detergent brands. Reynolds and Phillips (2005) provide a review of several brand equity measurement approaches and compare and contrast their properties against the theoretical underpinnings of brand equity (Keller 1993).

Brand Equity Measure

The mean annual brand equity index score for a brand was used as the overall indicator of a brand's equity (x-bar = 58.6,σ = 8.1).

Table 25: Descriptive Statistics of Equitrend Brand Equity Values Linked to BrandChat Database

	2007	2008
Mean	58.9	59.4
Median	59.1	59.5
SD	7.5	7.5
Skewness	–.01	–.17
Kurtosis	–.62	–.53
Minimum	41.6	40.5
Maximum	75.8	75.6
10th percentile	48.9	50.1
90th percentile	68.7	69.8
n	205	196

Table 26: Equitrend Brand Equity Brands Represented by Superbrands Category and Report Year

Superbrands Categories	2006	2007	2008	Grand Total
Alcohol	20			20
Apparel	11	11	8	30
Appliances	5	5	4	14
Auto		33		33
Autos	36		36	72
Beer, Wine, & Liquor		29	30	59
Beverages	18	18	20	56
Computers	13	15	10	38
Consumer Electronics	5	4	5	14
Cosmetics & Fragrances	22	20		42
Credit Cards	4	4	4	12
Entertainment	9	9	9	27
Fast Food / Restaurants	10	9	10	29
Financial Services	5	3	4	12
Food	52	43	41	136
Footwear	7	8	8	23
Health & Beauty	20	20	17	57
Household	25	25	23	73
Petrol	12	12		24
Pharmacy OTC	11	11	12	34
Pharmacy Prescription	9	9	9	27
Retail	10	10	10	30
Supermarkets	11	11	9	31
Telecommunications	6	6	6	18
Tobacco	10	10	10	30
Toys	5	5	5	15
Travel	23	23	25	71
World Wide Web	7	7		14
Grand Total	366	360	315	1041

Product Categories

Brands from the BrandChat database were organized into nine categories: consumer packaged goods, finance and insurance, Internet and telecom, retail, travel, automotive, computer, food service/restaurant, and other. These categorizations were derived according to three primary considerations: (1) categories should highlight conceptually distinct groupings of brands for which prior literature has shown the influence of WOM to operate similarly; (2) categories should contain a sufficient number of brands that strike a balance between being (a) not so fine as to make interpretation difficult and contingent on only a small number of brands in a category and (b) not so coarse as to make the brands within a category difficult to interpret; and (3) categories should be generally comparable to the those used by the BrandChat, Equitrend Brand Equity, and ACSI databases.

Potential categories to code brands into were first derived using all categorizations used by BrandChat, Equitrend, and ACSI. This created a potential category list of more than 55 categories. A logical grouping process was then performed; for example, all categories qualified as consumer packaged goods (e.g., beverages, food, personal care) were grouped together because they represented generally low-cost items frequently purchased, and all banking/finance/insurance services firms were grouped together because they represented services often difficult or infrequently switched to by consumers. This process reduced the potential categories to 12 possible groups. Then, two independent raters were shown all brands candidates for analysis from the BrandChat database. These coders were only shown the brand name and descriptions of the 12 possible categories. Coders were allowed to use the Internet to search for more information about brands if necessary. These coders were not shown the brand

categories used for brands by BrandChat, ACSI, and Equitrend. This process resulted in 90% agreement between the two coders. Brands with unmatched categories were then discussed between coders and referred against the original BrandChat categorizations to reach resolution. Of the 654 brands from the first investigation, the classification was as follows: 210 consumer packaged goods, 57 finance & insurance, 38 Internet & telecom, 77 retail, 32 travel, 42 automotive, 15 computer, 40 food service/restaurant, and 143 other.

Analyzed Sample

Not all brands from the first investigation were retained for this additional analyses because not all brands represented in the BrandChat database could be linked to brands represented in the ACSI. After the matching criteria discussed previously was applied, 148 brands were retained for this investigation. This represents 22.6% of the brands from the first investigation. The publicly traded brands in the ACSI can reasonably be expected to represent brands that are more well-known by virtue of their market positions. This also appears to be the case in terms of national WOM share, because despite the substantial reduction in the number of brands analyzed, 107,251 WOM conversations (56.9% of the conversations from the original analyses) were retained (average conversations per brand = 724.7, min = 30, max = 6,619).

A similar challenge emerged for linking the brands with brand equity scores to the BrandChat brands. The matching criteria discussed previously resulted in 226 brands retained for the brand equity investigation (34.5% of the original investigation) and 125,460 WOM conversations (66.6% of all WOM from original investigation).

ANALYSES AND RESULTS: INVESTIGATION 2

Equations 2 and 3 depict the structure of the two random coefficient regression models used to assess the hypotheses for the three dependent variables. The models shown are for purchase intentions ($BUY_{c,b}$), but it is the same for the other two dependent variables ($TRANSMIT_{c,b}$ & $SEEKINFO_{c,b}$). Table 27 provides a description of each variable listed in the random coefficient regression s that is new from the first investigation and how the variables are coded. Considerations for modeling cross-level interactions (WOM conversation being level 1 and brand-level characteristics of ACSI and brand equity being level 2) are discussed as well. Similar to Investigation 1, the model for purchase intentions included the three-way interactions between social tie, valence, and channel, while the models for retransmission and seek information excluded the three-way interactions.

Equation 2: Random Coefficient Regression Model: – Inclusion of Product Categories and ACSI Scores

$BUY_{c,b}$= [equation from investigation 1] +

$$(\gamma_{0,3}) * CatCPG_b + (\gamma_{0,4}) * CatFin_b + (\gamma_{0,5}) * CatInt_b + (\gamma_{0,6}) * CatRetail_b +$$

$$(\gamma_{0,7}) * CatTravel_b + (\gamma_{0,8}) * CatAuto_b + (\gamma_{0,9}) * CatComp_b + (\gamma_{0,10}) * CatFoodS_b +$$

$$(\gamma_{0,11}) * ASCI_b + (\gamma_{1,11}) * ValPos_{c,b} * ASCI_b + (\gamma_{2,11}) * ValNeg_{c,b} * ASCI_b + (\gamma_{3,11}) * ValMix_{c,b} * ASCI_b +$$

$$(\gamma_{4,11}) * ChnOffl_{c,b} * ASCI_b + (\gamma_{5,11}) * SocTS_{c,b} * ASCI_b + (\gamma_{6,11}) * SocTE_{c,b} * ASCI_b$$

Equation 3: Random Coefficient Regression Model – Inclusion of Product Categories and Brand Equity Scores

$BUY_{c,b}$= [equation from investigation 1] +

$$(\gamma_{0,3}) * CatCPG_b + (\gamma_{0,4}) * CatFin_b + (\gamma_{0,5}) * CatInt_b + (\gamma_{0,6}) * CatRetail_b +$$

$$(\gamma_{0,7}) * CatTravel_b + (\gamma_{0,8}) * CatAuto_b + (\gamma_{0,9}) * CatComp_b + (\gamma_{0,10}) * CatFoodS_b +$$

$$(\gamma_{0,11}) * BrEq_b + (\gamma_{1,11}) * ValPos_{c,b} * BrEq_b + (\gamma_{2,11}) * ValNeg_{c,b} * BrEq_b + (\gamma_{3,11}) * ValMix_{c,b} * BrEq_b +$$

$$(\gamma_{4,11}) * ChnOffl_{c,b} * BrEq_b + (\gamma_{5,11}) * SocTS_{c,b} * BrEq_b + (\gamma_{6,11}) * SocTE_{c,b} * BrEq_b$$

Table 27: Description of New Variables Used in Investigation 2

Variable Name	Description
$CatCPG_b$	Dummy code indicating a brand generally associated with the consumer packaged goods market.
$CatFin_b$	Dummy code indicating a brand generally associated with the finance and/or insurance services market.
$CatInt_b$	Dummy code indicating a brand generally associated with providing Internet and/or telecom services.
$CatRetail_b$	Dummy code indicating a brand generally associated with being a retail establishment.
$CatTravel_b$	Dummy code indicating a brand generally associated with providing vacation and travel services.
$CatAuto_b$	Dummy code indicating a brand generally associated with the automobile market.
$CatComp_b$	Dummy code indicating a brand generally associated with the computer hardware and/or software market.
$CatFoodS_b$	Dummy code indicating a brand generally associated with the food services market.
$ACSI_b$	Average ACSI score for a brand from years 2007 to 2009. Mean-centered to analyzed sample.
$BrEq_b$	Average Equitrend brand equity score for a brand from years 2006 to 2008. Mean-centered to analyzed sample.

Similar to the previous investigation, all coefficients denoted by $\gamma_{c,0}$ represent population regression coefficients for the respective level 1 (WOM conversation) predictors, and the $u_{0,\mathrm{b}}$ coefficients indicate that the main effects of all level 1 variables are allowed to deviate randomly from the population regression coefficient. The brand-level coefficients (level 2 variables) are denoted by $\gamma_{0,b}$, and the cross-level interactions are denoted by $\gamma_{c,b}$. This notation follows recommended procedures (Raudenbush and Bryk 2002).

When introducing level 2 predictors with cross-interactions in a mixed model, it is important to consider how to properly center level 1 variables, because inappropriate centering procedures can lead to spurious results that suggest a cross-level interaction when no such effect exists in the population. (Hofmann and Gavin [1998] show this using simulated data.) Centering the level 2 variables (product categories, ACSI, and brand equity) means only following typical recommended procedures for ordinary least squares regression (Enders and Tofighi 2007). From recommendations, level 1 predictors were CWC, level 2 dummy variables (product categories) were kept as dummy codes, and level 2 ACSI and Equitrend Brand Equity scores were mean-centered. The cross-level interactions were thus the product of the CWC level 1 variables and the respective level 2 variable. This approach leads to "a pure estimate of the moderating influence that a Level 2 predictor exerts on the Level 1 association between X and Y and cannot be distorted by the presence of an interaction that involves the cluster means of X" (Enders 2007, p. 133). One downside of this approach is that level 2 predictors and level 1 predictors are rendered orthogonal from one another, meaning that the level 2 main effects cannot be strictly interpreted as "partialing out the effect of" the level 1 variables.

In addition to the empirical models analyzed and reported here, another model was checked in which the product category of the brand had a cross-level interaction with the

valence, social tie, and channel of WOM. This approach considers the possibly that the overall magnitude of positive or negative sentiment would vary in particular categories (e.g., restaurants) or, for example, that how social ties influence purchase depends on the particular category (e.g., close interpersonal ties may be particularly important sources of influence for travel and vacation planning). None of these interactions were significant ($p > .05$) and this admittedly more speculative and less parsimonious model was subsequently not used for any further investigations.

Brand Clustering and Comparing Results with Previous Investigation

Before interpreting the results relating to the brand category covariates and the ACSI and brand equity hypotheses, a brief comparison of the empirical results with the original full sample investigation is in order. First, the ICC for the three dependent variables in the two samples analyzed for Investigation 2 are comparable to the original ICCs. For example, $ICC_{purchase}$ was .207 for the original investigation and was also .207 for the ACSI sample and .204 for the Equitrend brand equity sample. These results again indicate that there is substantial within-brand clustering for the intention to purchase ratings. ICC_{resend} was .067 in the original sample and was .061 (ACSI) and .072 (Equitrend) for the current investigation. Finally, $ICC_{seekinfo}$ was .098 originally and comparable in the new investigation (.093 for ACSI and .107 for Equitrend).

Almost all effects related to the hypotheses for Investigation 1 remain significant or nonsignificant in this smaller sample study, and the direction of all effects remained the same. However, the magnitude of the estimate for some of these parameters varied somewhat from the original analysis but did not alter any substantive conclusions from the first investigation with

one exception (discussed subsequently). Some of the instances in which there was a change of parameter significance at the p = .05 level were as follows: (1) In both subsamples, the three-way interactions between positive valence, offline channel, and strong social ties on purchase intentions were negative and significant (which actually would have provided full instead of partial support for $H_{5purchase}$), and in the Equitrend subsample the three-way interaction between negative, offline channel and strong social ties was negative and significant (which still supported the original $H_{5purchase}$); (2) the interaction between positive WOM and strong social ties on retransmission intentions was positive and significant (which would have been consistent with the original $H_{6retransmit}$) in the Equitrend subsample; and (3) the interaction between negative WOM and offline channel on intentions to seek additional information about a brand was no longer significant in the Equitrend subsample (inconsistent with $H_{4seekinfo}$), but the interaction between positive WOM and offline channel was significant (inconsistent with $H_{4seekinfo}$). This replicated analysis for both the ACSI and Equitrend subsamples is reported in Table 28 and Table 30, respectively. Correlations of random effects for the ACSI subsample is reported in Table 29, and random effect correlations for the Equitrend subsample is reported in Table 31.

Results for Investigation 2

H_1 hypothesizes that brands with higher levels of overall satisfaction would tend to result in positive WOM conversations about the brand to be even more impactful on purchase intentions than for brands with lower levels of customer satisfaction. In addition, brands with high overall levels of satisfaction were hypothesized also to have higher purchase intentions, even when the received WOM was negative, compared with brands with low levels of satisfaction. To test these hypotheses, the simple slope method was used with a formal z-test to

test for significant slope difference. As is typical with this approach, the slopes of brands +1 standard deviation (denoted as "high satisfaction brands") and –1 standard deviation (denoted as "low satisfaction brands") from the mean-centered ACSI score was used to derive the slope comparisons (–7.1 and +7.1).

The difference in the slope of negative WOM between higher satisfaction brands and low satisfaction brands was positive and significant ($\Delta\beta = .58$, $p < .05$), meaning high satisfaction brands tended to experience less harmful negative WOM, consistent with H_1. The main effect of ACSI was not significant, nor were any of the other interactions, inconsistent with H_1. In total, there was partial support for H_1—specifically, that brands with higher levels of overall satisfaction were somewhat insulated from the harmful impact of negative WOM even after controlling for the category of the brand, the brand's overall level of WOM volume (and interaction with the WOM sentiment), and the overall percentage of positive WOM about the brand.

Table 28: ACSI Original and Interaction Models Compared Side-by-Side (Six Models)

		Intent to Purchase		Intent to Retransmit		Intent to Seek Info	
		Replication	Category Variances and ACSI	Replication	Category Variances and ACSI	Replication	Category Variances and ACSI
$\gamma_{0,0}$	Intercept	7.23 (.095)***	7.10 (.136)***	7.27 (.050)***	7.19 (.095)***	5.77 (.077)***	5.86 (.137)***
$\gamma_{1,0}$	Positive (valence)	1.60 (.102)***	1.60 (.103)***	1.75 (.087)***	1.75 (.087)***	1.73 (.096)***	1.73 (.097)***
$\gamma_{2,0}$	Negative (valence)	–2.58 (.187)***	–2.57 (.186)***	.74 (.124)***	.74 (.123)***	–.82 (.156)***	–.82 (.156)***
$\gamma_{3,0}$	Mixed (valence)	–.26 (.100)**	–.26 (.101)**	.75 (.103)***	.75 (.104)***	.53 (.107)***	.53 (.107)***
$\gamma_{4,0}$	Offline (channel)	.11 (.063)	.10 (.063)	.10 (.083)	.10 (.084)	–.36 (.078)***	–.35 (.078)***
$\gamma_{5,0}$	Strong (social tie)	.51 (.041)***	.51 (.041)***	.11 (.042)**	.11 (.043)**	.25 (.053)***	.25 (.053)***
$\gamma_{6,0}$	Expert (social tie)	.85 (.106)***	.89 (.108)***	.35 (.096)***	.36 (.095)***	.76 (.108)***	.77 (.108)***
$\gamma_{7,0}$	Positive × Offline	.18 (.054)***	.18 (.054)***	.46 (.053)***	.45 (.053)***	–.05 (.060)	–.05 (.060)
$\gamma_{8,0}$	Negative × Offline	–.51 (.069)***	–.51 (.069)***	.33 (.068)***	.33 (.068)***	–.47 (.076)***	–.47 (.076)***
$\gamma_{9,0}$	Mixed × Offline	–.18 (.061)**	–.18 (.061)**	.29 (.060)***	.29 (.060)***	–.11 (.068)	–.11 (.068)
$\gamma_{10,0}$	Positive × Strong	–.10 (.029)***	–.10 (.029)***	.04 (.029)	.04 (.029)	–.21 (.033)***	–.21 (.033)***
$\gamma_{11,0}$	Negative × Strong	–.13 (.039)***	–.13 (.039)***	–.04 (.039)	–.04 (.039)	–.20 (.044)***	–.20 (.044)***
$\gamma_{12,0}$	Mixed × Strong	–.10 (.033)**	–.10 (.033)**	–.01 (.033)	–.02 (.033)	–.12 (.037)***	–.12 (.037)***
$\gamma_{13,0}$	Positive × Expert	–.46 (.073)***	–.46 (.073)***	–.20 (.072)**	–.20 (.072)**	–.34 (.081)***	–.34 (.081)***
$\gamma_{14,0}$	Negative × Expert	–.67 (.099)***	–.66 (.099)***	–.23 (.097)*	–.24 (.097)*	–.31 (.110)**	–.31 (.110)**
$\gamma_{15,0}$	Mixed × Expert	–.16 (.086)	–.16 (.086)	–.22 (.084)**	–.22 (.084)**	–.08 (.095)	–.08 (.095)
$\gamma_{16,0}$	Strong × Offline	.12 (.042)**	.12 (.042)**	.10 (.041)*	.10 (.041)**	.32 (.047)***	.32 (.047)***
$\gamma_{17,0}$	Expert × Offline	.23 (.095)*	.23 (.095)*	.05 (.094)	.05 (.094)	.25 (.106)*	.26 (.106)*
$\gamma_{18,0}$	Positive × Offline × Strong	–.33 (.132)*	–.33 (.132)*				
$\gamma_{19,0}$	Negative × Offline × Strong	–.16 (.166)	–.16 (.166)				
$\gamma_{20,0}$	Mixed × Offline × Strong	–.44 (.146)**	–.44 (.146)**				
$\gamma_{21,0}$	Positive × Offline × Expert	.32 (.279)	.32 (.279)				
$\gamma_{22,0}$	Negative × Offline × Expert	.47 (.366)	.48 (.366)				
$\gamma_{23,0}$	Mixed*Offline × Expert	.71 (.318)*	.71 (.318)*				
$\gamma_{0,1}$	WOM Volume	.00 (.000)	.00 (.000)	–.00 (.000)	.00 (.000)	–.00 (.000)	–.00 (.000)
$\gamma_{1,1}$	WOM Volume × Positive	–.00 (.000)	–.00 (.000)	.00 (.000)	.00 (.000)	.00 (.000)	.00 (.000)
$\gamma_{2,1}$	WOM Volume × Negative	.00 (.000)	.00 (.000)	.00 (.000)	.00 (.000)	.00 (.000)	.00 (.000)
$\gamma_{3,1}$	WOM Volume × Mixed	–.00 (.000)	–.00 (.000)	–.00 (.000)	–.00 (.000)	–.00 (.000)	–.00 (.000)
$\gamma_{0,2}$	Positive WOM %	.05 (.004)***	.04 (.004)***	.01 (.002)***	.01 (.003)***	.01 (.003)*	.02 (.004)***
$\gamma_{1,2}$	Positive WOM % × Positive	–.00 (.004)	–.01 (.006)	.00 (.004)	.00 (.005)	.00 (.004)	.00 (.006)
$\gamma_{2,2}$	Positive WOM % × Negative	–.00 (.008)	–.02 (.011)*	–.02 (.006)***	–.02 (.008)**	.02 (.007)**	.01 (.010)
$\gamma_{3,2}$	Positive WOM % × Mixed	–.00 (.004)	–.00 (.006)	–.00 (.004)	–.00 (.006)	.00 (.005)	.00 (.007)
$\gamma_{0,3}$	CPG (dummy)		.55 (.158)***		–.19 (.112)		–.91 (.160)***
$\gamma_{0,4}$	Finance & Insurance (dummy)		.02 (.165)		.17 (.118)		.43 (.168)**
$\gamma_{0,5}$	Internet & Telecom (dummy)		.02 (.151)		.35 (.107)***		.36 (.153)*
$\gamma_{0,6}$	Retail (dummy)		.69 (.142)***		.28 (.101)**		–.10 (.145)
$\gamma_{0,7}$	Travel (dummy)		.47 (.172)**		.42 (.122)***		.19 (.175)
$\gamma_{0,8}$	Automotive (dummy)		–.86 (.159)***		–.16 (.113)		.04 (.162)
$\gamma_{0,9}$	Computer (dummy)		–.15 (.191)		.16 (.135)		.46 (.194)*
$\gamma_{0,10}$	Restaurant (dummy)		.74 (.163)***		–.00 (.115)		–.66 (.165)***
$\gamma_{0,11}$	ACSI		.00 (.009)		–.00 (.006)		.00 (.009)
$\gamma_{1,11}$	ACSI × Positive		.01 (.011)		–.00 (.010)		–.00 (.011)
$\gamma_{2,11}$	ACSI × Negative		.04 (.020)*		–.00 (.014)		.01 (.017)
$\gamma_{3,11}$	ACSI × Mixed		–.00 (.011)		–.00 (.011)		.01 (.012)
$\gamma_{4,11}$	ACSI × Offline		–.00 (.008)		.01 (.011)		.00 (.011)
$\gamma_{5,11}$	ACSI × Strong		.00 (.005)		–.00 (.006)		–.00 (.007)
$\gamma_{6,11}$	ACSI × Expert		.01 (.014)		.02 (.012)		.01 (.014)
	Model Fit						
	LL (k)	–173513.7 (46)	–173477.0 (61)	–172083.7 (40)	–172082.7 (55)	–185365.5 (40)	–185346.4 (55)
	AIC	347119.4	347075.9	344247.4	344275.4	370811.0	370802.9
	BIC	347560.2	347660.5	344630.7	344802.5	371194.3	371329.9

* *p* < .05, two-tailed.; ** *p* < .01, two-tailed.; *** p<.001, two-tailed.

n = 107,251 conversations, 148 brands.. Time covariates ($\gamma 24{,}0 – \gamma 37{,}0$) suppressed from output for space.

Table 29: Correlations of ACSI Model Investigation 2: Random Effects – Dependent Variables

	Intercept	Positive	Negative	Mixed	Offline	Strong
Intercept						
Positive	–.29, –.08, –.06					
Negative	–.01, –.05, –.09	.49, .47, .59				
Mixed	.09, .09, .02	.59, .67, .60	.57, .35, .42			
Offline	.18, .32, .28	–.09, –.06, .17	.10, .08, .22	.05, .05, .28		
Strong	–.23, –.16, –.12	.16, .16, .11	.04, –.04, .05	–.13, .19, .03	–.11, –.14, .04	
Expert	–.29, –.14, –.02	.28, .26, .18	.21, –.04, .08	.13, .21, .06	.03, .01, .01	.46, .21, .34

Correlations of random effects reported for full models only. Purchase intentions reported first, retransmission second, and seeking information third.

H_2 hypothesizes that when brands with high levels of overall satisfaction are compared with brands with lower levels of overall satisfaction, positive WOM conversations about the brand would result in more retransmission of the message when positive and less intention to retransmit the message when the WOM was negative. This hypothesis was not supported: The difference in slope of positive and negative WOM between brands with high and low overall levels of satisfaction was not significant. In contrast, the covariate of the interaction between the percentage of positive WOM a brand has and negatively valenced WOM was negative and significant ($\gamma_{2,2} = -.02$, $p < .001$), and the main effect of the percentage of positive WOM was positive and significant ($\gamma_{0,2} = .01$, $p < .001$). Thus, after controlling for overall brand satisfaction and its interaction with WOM valence as well as product category, brands with higher overall levels of positive WOM tend to have their WOM retransmitted when the WOM is neutral, mixed, or positive, but this effect is attenuated in the case of negative WOM. Thus, one possible explanation for the lack of support for H_2 is that the overall current customer satisfaction level for a brand is not significant in explaining WOM retransmission, but the current level of positive buzz about a brand is.

H_3 states that consumers would seek additional information about a brand with higher levels of overall satisfaction than for a low-satisfaction brand when the WOM episode contained either positive or negative sentiment about the brand. This hypothesis was not supported: Neither the main effect of the ACSI score nor the interaction of ACSI and positive or negative WOM was significant.

H_4–H_7 involve the role of brand equity on the three dependent variables and its moderating influence of WOM conversation characteristics on the dependent variables The results from the these models are reported in Table 30. H_4 involves how overall brand equity

may be expected to modify the influence of a particular WOM episode about the brand on a WOM recipient's purchase intentions. Brands with strong equity in general were hypothesized to have greater purchase intentions from a particular WOM episode when the valence of the WOM conversation about the brand was either negative or positive. There was partial support for this hypothesis. There was a strong positive main effect of brand equity on purchase intentions ($\gamma_{0,11}$ = .01, p < .001). However, there was a negative interaction between positive WOM and brand equity ($\gamma_{1,11}$ = –.02, p < .001). This result suggests that the beneficial effect enjoyed by brands with high levels of brand equity compared with brands with lower equity was true in the case of negative, mixed, or neutral WOM. However, in the case of positive WOM, weak brands actually reaped more impactful WOM. This unhypothesized effect may be interpreted as consistent with the idea that weak brands are particularly reliant on explicit, direct positive news from the mouths of other consumers, while such forms of WOM are less impactful for already strong brands. Conversely, considering that the large positive effect of positive WOM already places estimates near the maximum possible score on the intentions to purchase scale, this attenuating interaction may be a reflection of a ceiling effect of measuring purchase intentions about the brand (Peterson and Wilson 1992). Figure 18 plots the relationship between WOM valence (positive, negative, neutral, and mixed) on purchase intentions across brands with low brand equity (–1 SD, or –8.1 points from mean), average, and high (+1 SD, or +8.1 points).

Table 30: Brand Equity Original and Interaction Models Compared Side-by-Side (Six Models)

		Intent to Purchase		Intent to Retransmit		Intent to Seek Info	
		Replication	Category Variances and Brand Equity	Replication	Category Variances and Brand Equity	Replication	Category Variances and Brand Equity
$\gamma_{0,0}$	Intercept	7.43 (.084)***	7.36 (.087)***	7.28 (.052)***	7.36 (.074)***	5.77 (.077)***	6.02 (.096)***
$\gamma_{1,0}$	Positive (valence)	1.57 (.085)***	1.57 (.085)***	1.77 (.098)***	1.77 (.098)***	1.72 (.103)***	1.72 (.104)***
$\gamma_{2,0}$	Negative (valence)	–2.58 (.212)***	–2.58 (.214)***	.63 (.170)***	.63 (.170)***	–.73 (.185)***	–.74 (.184)***
$\gamma_{3,0}$	Mixed (valence)	–.34 (.106)**	–.34 (.106)**	.77 (.105)***	.77 (.104)***	.52 (.121)***	.52 (.120)***
$\gamma_{4,0}$	Offline (channel)	.13 (.067)*	.16 (.067)*	–.00 (.071)	.00 (.073)	–.39 (.084)***	–.38 (.087)***
$\gamma_{5,0}$	Strong (social tie)	.58 (.042)***	.56 (.042)***	.18 (.044)***	.17 (.045)***	.34 (.063)***	.30 (.063)***
$\gamma_{6,0}$	Expert (social tie)	.60 (.101)***	.62 (.106)***	.30 (.090)***	.28 (.093)**	.86 (.127)***	.77 (.130)***
$\gamma_{7,0}$	Positive × Offline	.27 (.053)***	.27 (.053)***	.39 (.052)***	.39 (.052)***	.12 (.059)*	.12 (.059)*
$\gamma_{8,0}$	Negative × Offline	–.45 (.068)***	–.45 (.068)***	.39 (.068)***	.39 (.068)***	–.21 (.077)**	–.21 (.077)**
$\gamma_{9,0}$	Mixed × Offline	–.20 (.060)***	–.20 (.060)***	.23 (.059)***	.22 (.059)***	–.00 (.067)	.00 (.067)
$\gamma_{10,0}$	Positive × Strong	–.17 (.028)***	–.17 (.028)***	.06 (.028)*	.06 (.028)*	–.15 (.032)***	–.15 (.032)***
$\gamma_{11,0}$	Negative × Strong	–.15 (.038)***	–.15 (.038)***	.00 (.038)	.00 (.038)	–.06 (.044)	–.06 (.044)
$\gamma_{12,0}$	Mixed × Strong	–.11 (.032)***	–.11 (.032)***	.08 (.032)**	.08 (.032)**	–.07 (.036)*	–.07 (.036)*
$\gamma_{13,0}$	Positive × Expert	–.48 (.076)***	–.48 (.076)***	–.28 (.076)***	–.28 (.076)***	–.46 (.086)***	–.46 (.086)***
$\gamma_{14,0}$	Negative × Expert	–.71 (.105)***	–.71 (.105)***	–.42 (.104)***	–.42 (.104)***	–.29 (.118)*	–.29 (.118)*
$\gamma_{15,0}$	Mixed × Expert	–.11 (.090)	–.11 (.090)	–.19 (.089)*	–.19 (.089)*	–.14 (.102)	–.14 (.102)
$\gamma_{16,0}$	Strong × Offline	.14 (.041)***	.14 (.041)***	.04 (.040)	.04 (.040)	.25 (.046)***	.25 (.046)***
$\gamma_{17,0}$	Expert × Offline	.26 (.095)**	.26 (.095)**	–.02 (.095)	–.02 (.095)	.13 (.108)	.13 (.108)
$\gamma_{18,0}$	Positive × Offline × Strong	–.29 (.129)*	–.29 (.129)*				
$\gamma_{19,0}$	Negative × Offline × Strong	–.32 (.164)*	–.32 (.164)*				
$\gamma_{20,0}$	Mixed × Offline × Strong	–.68 (.144)***	–.68 (.144)***				
$\gamma_{21,0}$	Positive × Offline × Expert	.29 (.277)	.29 (.277)				
$\gamma_{22,0}$	Negative × Offline × Expert	.42 (.370)	.43 (.370)				
$\gamma_{23,0}$	Mixed × Offline × Expert	.11 (.319)	.11 (.319)				
$\gamma_{0,1}$	WOM Volume	.00 (.000)	.00 (.000)	–.00 (.000)	–.00 (.000)	.00 (.000)	.00 (.000)
$\gamma_{1,1}$	WOM Volume × Positive	–.00 (.000)	–.00 (.000)	–.00 (.000)	–.00 (.000)	.00 (.000)	.00 (.000)
$\gamma_{2,1}$	WOM Volume × Negative	.00 (.000)	.00 (.000)	.00 (.000)	.00 (.000)	.00 (.000)	.00 (.000)
$\gamma_{3,1}$	WOM Volume × Mixed	–.00 (.000)	–.00 (.000)	–.00 (.000)	–.00 (.000)	.00 (.000)	–.00 (.000)
$\gamma_{0,2}$	Positive WOM %	.05 (.003)***	.03 (.003)***	.01 (.002)***	.01 (.002)***	.00 (.003)	.01 (.003)***
$\gamma_{1,2}$	Positive WOM % × Positive	–.01 (.003)***	–.01 (.004)*	.00 (.004)	.00 (.004)	.00 (.004)	.00 (.005)
$\gamma_{2,2}$	Positive WOM % × Negative	–.00 (.009)	.00 (.010)	–.01 (.007)**	–.02 (.008)**	.01 (.008)*	.01 (.009)
$\gamma_{3,2}$	Positive WOM % × Mixed	–.01 (.004)*	–.01 (.005)	–.00 (.004)	–.00 (.005)	.00 (.005)	–.00 (.006)
$\gamma_{0,3}$	CPG (dummy)		.43 (.083)***		–.21 (.072)**		–.79 (.094)***
$\gamma_{0,4}$	Finance & Insurance (dummy)		–.15 (.155)		–.06 (.136)		.11 (.177)
$\gamma_{0,5}$	Internet & Telecom (dummy)		–.34 (.137)*		.17 (.120)		.16 (.157)
$\gamma_{0,6}$	Retail (dummy)		.58 (.116)***		.21 (.101)*		–.26 (.132)*
$\gamma_{0,7}$	Travel (dummy)		.26 (.114)*		.19 (.100)*		.26 (.130)*
$\gamma_{0,8}$	Automotive (dummy)		–.95 (.118)***		–.43 (.103)***		–.03 (.134)
$\gamma_{0,9}$	Computer (dummy)		–.12 (.190)		.05 (.168)		.40 (.220)
$\gamma_{0,10}$	Restaurant (dummy)		.59 (.137)***		–.22 (.119)		–.84 (.156)***
$\gamma_{0,11}$	Brand Equity		.01 (.004)***		–.00 (.004)		.00 (.005)
$\gamma_{1,11}$	Brand Equity × Positive		–.02 (.007)**		.00 (.008)		.00 (.008)
$\gamma_{2,11}$	Brand Equity × Negative		–.00 (.017)		.00 (.014)		.03 (.015)*
$\gamma_{3,11}$	Brand Equity × Mixed		–.00 (.008)		.01 (.008)*		.02 (.010)**
$\gamma_{4,11}$	Brand Equity × Offline		.01 (.008)*		.00 (.009)		.00 (.011)
$\gamma_{5,11}$	Brand Equity × Strong		–.01 (.005)		–.00 (.005)		–.02 (.008)***
$\gamma_{6,11}$	Brand Equity × Expert		–.01 (.013)		–.01 (.012)		–.03 (.016)*
	Model Fit						
	LL (k)	–206259.0 (46)	–206202.5 (61)	–205637.3 (40)	–205647.1 (55)	–222018.1 (40)	–221986.2 (55)
	AIC	412610.0	412527.0	411354.5	411404.3	444116.3	444082.5
	BIC	413058.0	413121.1	411744.1	411939.9	444505.9	444618.1

* *p* < .05, two-tailed.; ** *p* < .01, two-tailed.; *** *p* < .001, two-tailed.

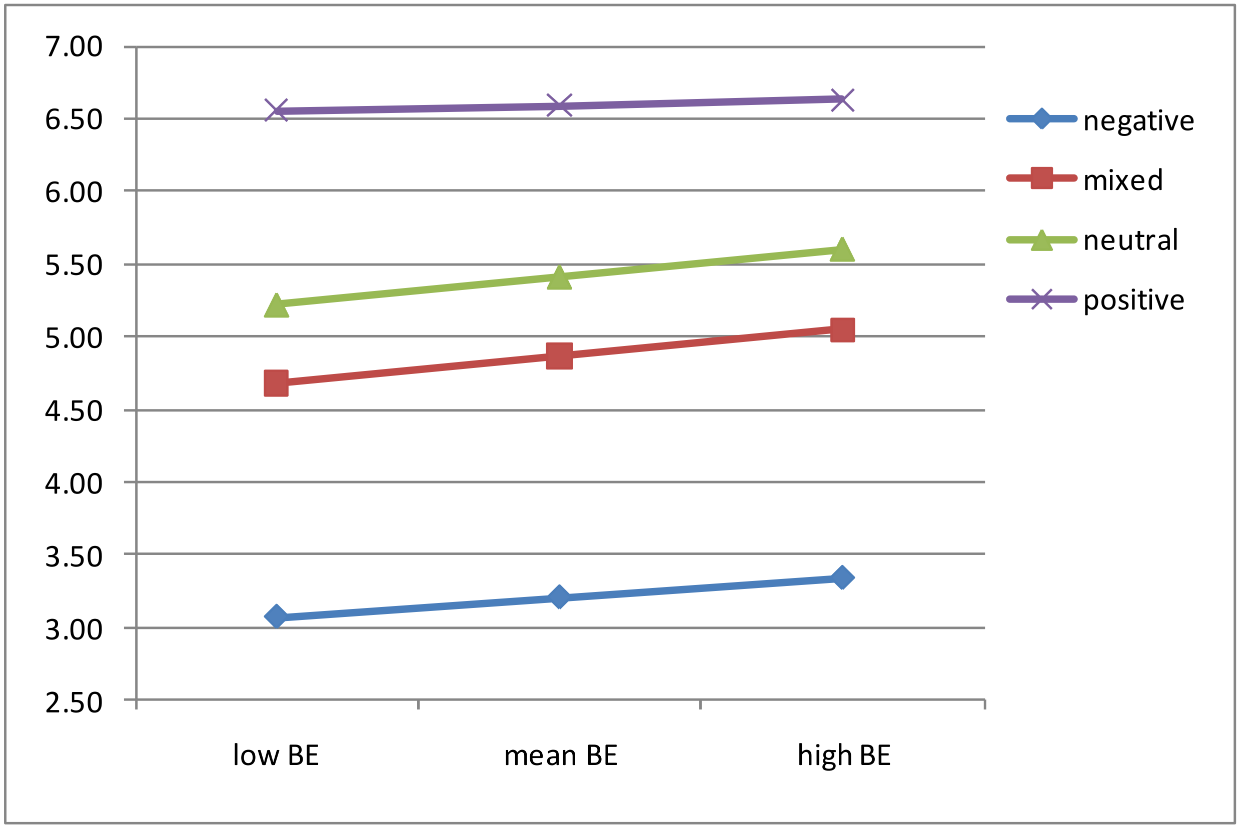
n = 125,460 conversations, 226 brands .Time covariates ($\gamma_{24,0}$ – $\gamma_{37,0}$) suppressed from output for space.

Table 31: Correlations of Brand Equity Model Investigation 2 - Random Effects – DV

	Intercept	Positive	Negative	Mixed	Offline	Strong
Intercept						
Positive	–.33, .08, .12					
Negative	–.02, .15, .03	.44, .61, .49				
Mixed	–.01, .15, .09	.57, .77, .69	.41, .59, .43			
Offline	.14, .10, .17	–.12, .01, .04	.09, .16, –.01	–.07, .01, –.14		
Strong	–.09, –.10, .01	.22, .06, –.04	–.01, .15, –.03	–.02, –.13, –.06	.05, .08, .10	
Expert	–.24, –.05, .07	.19, .11, .20	–.03, .08, .07	.10, .01, –.15	.29, .14, .30	.42, .22, .44

Correlations of random effects reported for full models only. Purchase intentions reported first, retransmission second, and seeking information third.

Figure 18: Relationship Between WOM Valence and Brand Strength (Equitrend Brand Equity) on Purchase Intentions

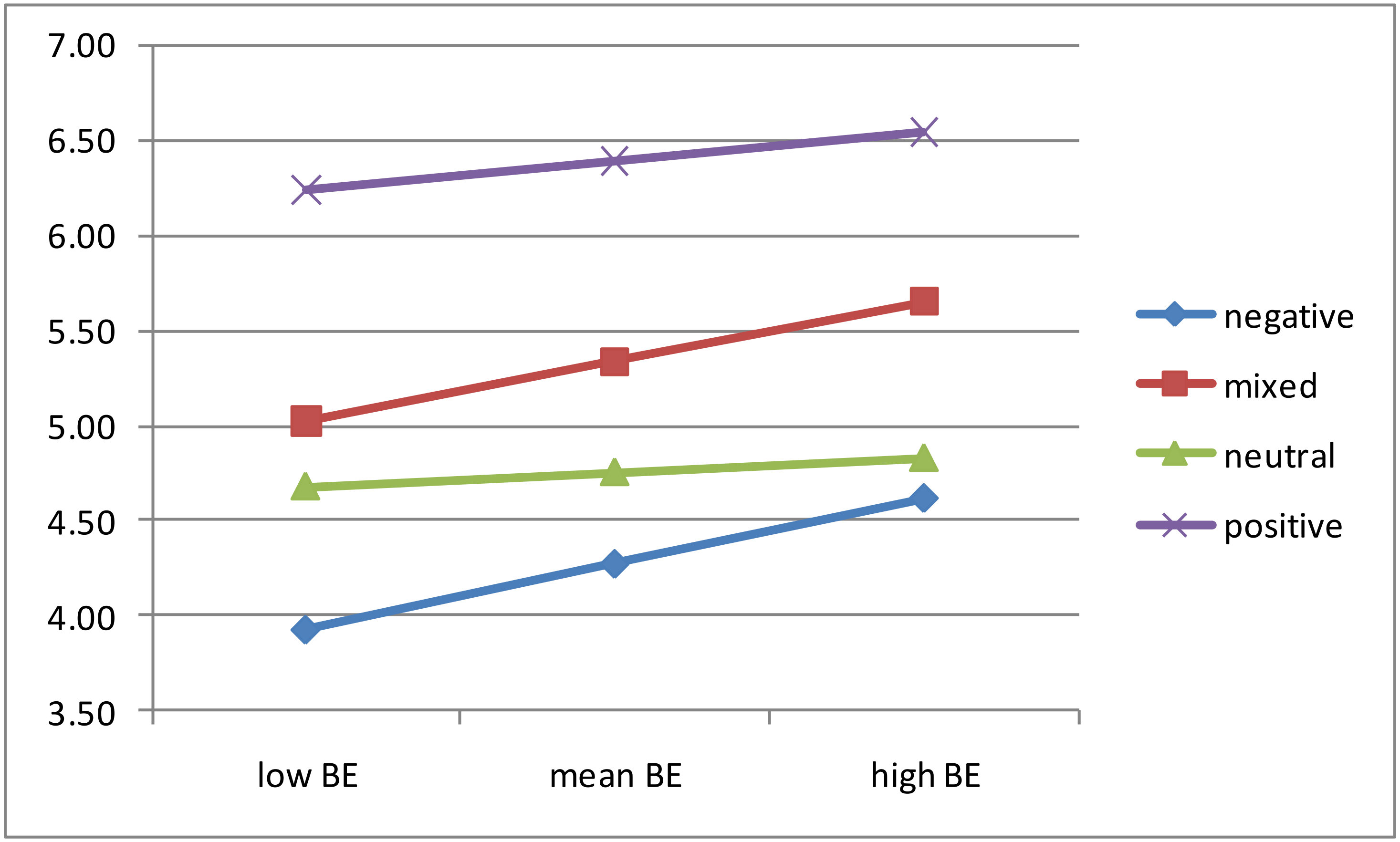


H_5 states that brands with generally higher levels of brand equity should be associated with higher levels of WOM retransmission if a WOM episode was positive about the brand and would have less WOM retransmission likelihood (than brands with lower brand equity) when the WOM message about the brand was negative. This hypothesis was not supported; there was no positive main effect of overall brand equity on message retransmission ($\gamma_{0,11}$ = —.00, $p > .05$), nor was there any significant interaction between overall brand equity and positive or negative WOM ($\gamma_{1,11}$; $\gamma_{2,11}$, $p > .05$). Brand equity positively interacted with mixed WOM about a brand ($\gamma_{3,11} = .01$, $p < .05$), which implies that the positive slope of mixed WOM on retransmission intentions becomes even more positive for brands with higher levels of brand equity. A possible explanation for this unsupported hypothesis is that the overall positive WOM sentiment about a brand is more important in influencing further WOM retransmission intentions than the brand equity of the brand. There was a significant main effect of positive WOM percentage on retransmission ($\gamma_{0,2} = .01$, $p < .001$) as well as a significant negative interaction between positive WOM percentage and negative WOM sentiment ($\gamma_{2,2} = –.02$, $p < .01$), implying that all types of WOM are more likely to be retransmitted for brands with higher ratios of positive WOM overall, except negative WOM, which is even less likely to be retransmitted.

H_6 states that brands with high levels of overall equity would have WOM conversations that resulted in WOM recipients seeking out additional information about the brand to a greater extent than for brands with lower levels of overall equity. This effect was hypothesized to be particularly strong when the message received about the brand was either positive or negative. This hypothesis was generally supported. There was a positive interaction between negative WOM and brand equity ($\gamma_{2,11} = .03$, $p < .05$), and there was a positive interaction between mixed WOM and overall brand equity ($\gamma_{3,11} = .02$, $p < .01$). This effect indicates that the negative slope

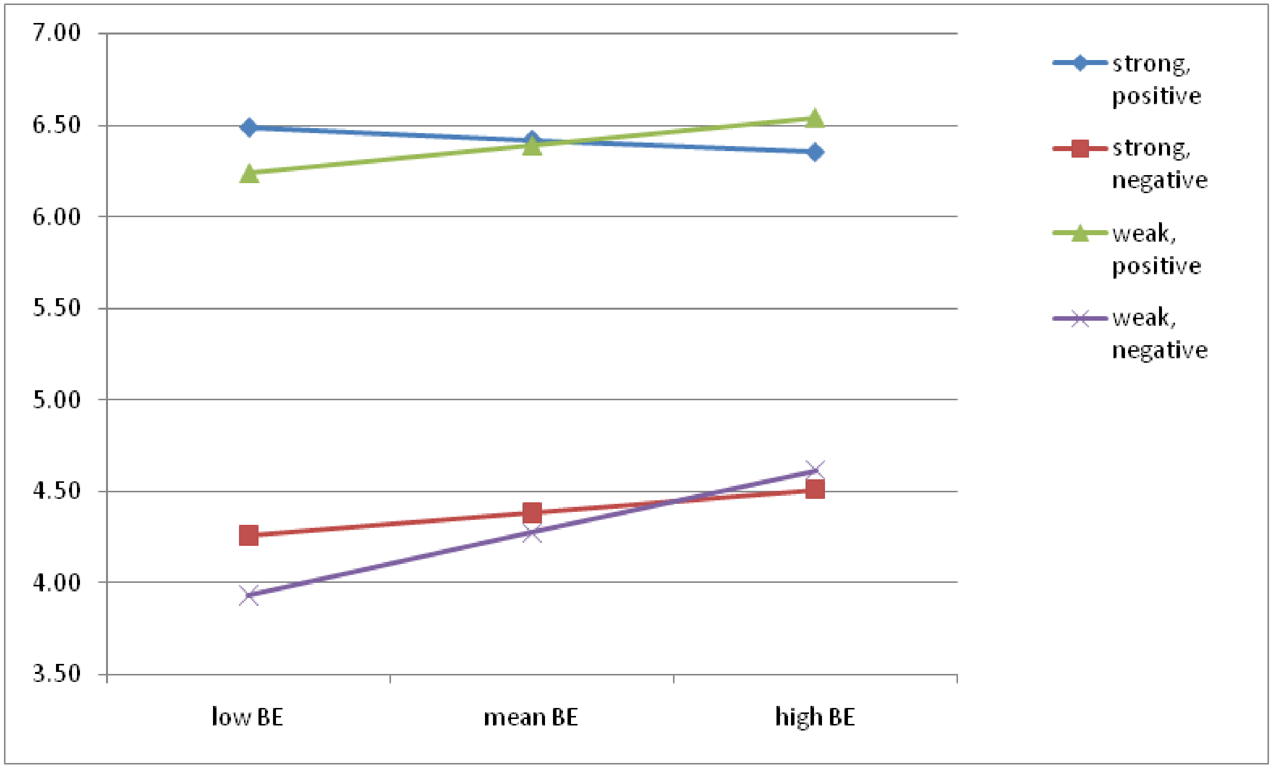
of negative WOM on seek information intentions is less steep for stronger brands and the positive slope of mixed WOM is even further accentuated for stronger brands. These results suggest that when WOM carries some negative component, stronger brands tend to motivate more additional information search. Figure 19 plots the moderating influence of low, medium, and high brand equity on WOM valence’s influence on information search.

Figure 19: The Relationship Between WOM Valence and Brand Strength (Equitrend Brand Equity) on Intentions to Seek Additional Information



H_7 involves how the social tie strength may differentially influence purchase intentions and additional information search depending on the overall strength of the brand. The hypothesis states that strong brands will be less dependent on the strength of the social tie to motivate WOM recipients to either purchase a brand or seek additional information about a brand. This hypothesis was supported in the case of seeking additional information but was not supported in the case of purchase. Specifically, there was a negative interaction between strong social ties and brand strength ($\gamma_{5,11} = -.02$, $p < .001$), attenuating the positive main effect of strong social tie on intentions to seek additional information. Plotting the effect of social tie strength for positive and negative WOM on intentions to seek additional information across low, medium, and high levels of overall brand equity demonstrates this relationship (Figure 20). It is noteworthy that this attenuating effect is also true in the case of expert opinions in terms of motivating additional information search ($\gamma_{6,11} = -.03$, $p < .05$), meaning that strong brands also need not rely as much on expert influence to motivate additional information search, a result also consistent (but not hypothesized) with the theory motivating H_7.

Figure 20: Relationship Between WOM Social Tie Strength and Brand Strength (Equitrend Brand Equity) on Intentions to Seek Additional Information for Positive and Negative WOM



H_8 specifies that there will be general differences in purchase intentions for brands depending on their product category and that there will be less of a difference in terms of WOM recipient intentions to retransmit or seek additional brand information. Consistent with expectations, the category the brand primarily operated in had a substantial influence on purchase intentions. For example, as expected, WOM about restaurants or quick service restaurants brands was substantially more likely to result in recipients buying or trying the product than brands in other categories ($\gamma_{0,10}$ = .74, $p < .001$ in the ACSI model; $\gamma_{0,10}$ = .59, $p < .001$ in the brand equity model). The lower-cost category of consumer packaged goods also had a higher mean level of purchase intentions ($\gamma_{0,3}$ = .55, $p < .001$ in the ACSI model; $\gamma_{0,3}$ = .43, $p < .001$ in the brand equity model), as well as retail establishments ($\gamma_{0,6}$ = .69, $p < .001$ in the ACSI model; $\gamma_{0,6}$ = .58, $p < .001$ in the brand equity model). Also consistent with the hypothesis, categories typified with high switching barriers and high cost had substantially lower overall purchase intentions: automotive ($\gamma_{0,8}$ = –.86, $p < .001$ in the ACSI model; $\gamma_{0,8}$ = –.95, $p < .001$ in the brand equity model) and Internet and telecom ($\gamma_{0,5}$ = –.34, $p < .05$ in the brand equity model).. The results regarding restaurants seem consistent with common restaurant management wisdom and previous studies of engineered WOM (Godes and Mayzlin 2009) that WOM is a critical driver of behavior.

H_8 also specifies that there would be fewer product category differences in a WOM recipient's intentions to retransmit the message or seek additional information about the brand. This was generally true in the case of intentions to seek additional information, with a few exceptions. Consumer packaged goods and restaurants both were substantially lower on intentions to seek additional information (consumer packaged goods: $\gamma_{0,1}$ = –.91, $p < .001$ in the ACSI model; $\gamma_{0,1}$ = –.79, $p < .001$ in the brand equity model; restaurants: $\gamma_{0,8}$ = –.66, $p < .001$ in

the ACSI model; $\gamma_{0,8}$ = -.84, $p < .001$ in the brand equity model). These results suggest that though people are much more likely to simply buy or try a consumer packaged goods or restaurant as a result of a WOM message, they are less likely to go out and engage in information search.

Table 32 briefly summarizes the results of the hypothesis tests. The following section elaborates on the results of this investigation and puts them in context with extant marketing research. I conclude with a discussion of implications for marketing management practice, limitations of this study, and directions for future inquiry.

Table 32: Summary of Hypotheses Results for Investigation 2

Hypothesis	Outcome
H_1 *(overall brand satisfaction moderates WOM valence on purchase intentions)*	Partially supported (insulated from negative WOM). Brands with higher levels of overall satisfaction are less negatively affected by a negative WOM episode.
H_2 *(overall brand satisfaction moderates WOM valence on retransmission intentions)*	Not supported.
H_3 *(overall brand satisfaction moderates WOM valence on seek information intentions)*	Not supported.
H_4 *(overall brand equity moderates WOM valence on purchase intentions)*	Partially supported. Strong brands reap benefits from neutral, mixed, and negative WOM. Unexpectedly, the effect flips for positive WOM (weak brands receive greater benefit from positive WOM).
H_5 *(overall brand equity moderates WOM valence on retransmission intentions)*	Not supported.
H_6 *(overall brand equity moderates WOM valence on seek information intentions)*	Supported. Strong brands experience greater impact of negative and mixed WOM on seek information intentions than weaker brands.
H_7 *(overall brand equity moderates WOM social tie on purchase intentions and seek information intentions)*	Partially supported. There was no support for strong brands having stronger impact on purchase intentions when the WOM was from weak ties. However, stronger brands motivated more brand information search when the WOM was from weak ties.
H_8 *(Brand product category moderates influence on purchase, retransmission, and seek information intentions)*	Partially supported. Purchase intentions were higher for consumer packaged goods and retail and lower for automotive and Internet & telecom. However, some categories expected to have significant differences were not significant, particularly in the case of retransmission and seek information intentions.

DISCUSSION AND IMPLICATIONS FOR INVESTIGATION 2

Implications for Marketing Research

This investigation demonstrates that the impact of WOM on immediate consumer response varies depending on the market-based assets of aggregate customer satisfaction and brand equity. The literature on these market-based assets has long speculated that beneficial WOM is one of the processes by which cultivating these assets reaps rewards for brand managers. However, this literature has tended to focus on the volume of positive and negative WOM production (strong brands create more positive WOM and less negative WOM). This current investigation proposes a different novel mechanism by which these market-based assets influence brand performance: The potency of individual WOM episodes tends to favor strong brands over weaker brands. Thus, a strong brand and weak brand with equivalent WOM volumes may nonetheless experience differential impacts from WOM. These results were observed after controlling for brands' WOM volume levels and their level of positive WOM compared with all WOM generated about the brand.

The insights of this investigation complement the notion that positive and negative WOM volumes fluctuate across aggregate customer satisfaction and brand equity. To consider this possibility, I plotted positive and negative WOM volume of the brands represented in the BrandChat database across ACSI scores and Equitrend brand equity scores, respectively. The correlation between ACSI/brand equity score and WOM volume was consistent with expectations but weak: The correlation between positive WOM and ACSI and brand equity was .12 and .15, respectively; the correlation between negative WOM and ACSI and brand equity was –.12 and –.04, respectively).

Figure 21 andFigure 22 provide a simplified illustration of this point by plotting the mean volume of annual brand positive and negative WOM across deciles of ACSI and Equitrend brand equity scores, respectively. In short, these results suggest that it is incorrect, or at least incomplete. to assume that these two market-based assets solely drive future brand performance on the basis of fluctuating WOM volumes. The current study indicates that WOM impact may be a superior, or at least complementary, answer. Further inquiries linking WOM and market-based assets on brand performance should thus incorporate the systematic variance in the impact of WOM episodes across aggregate levels of satisfaction and brand equity.

Figure 21: Average Brand Annual Positive and Negative WOM by ACSI Decile

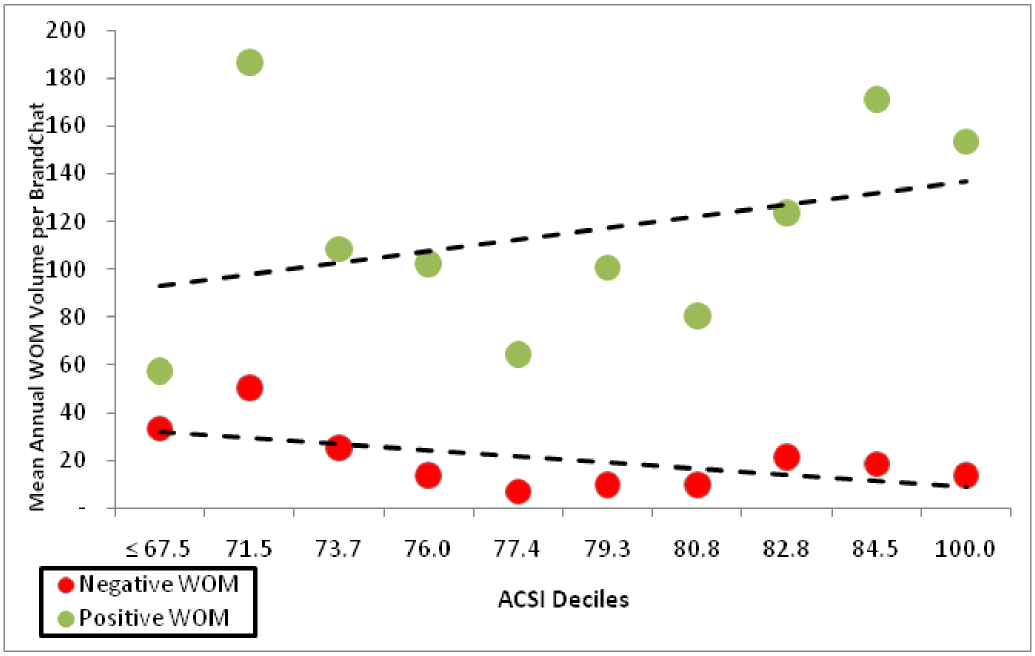
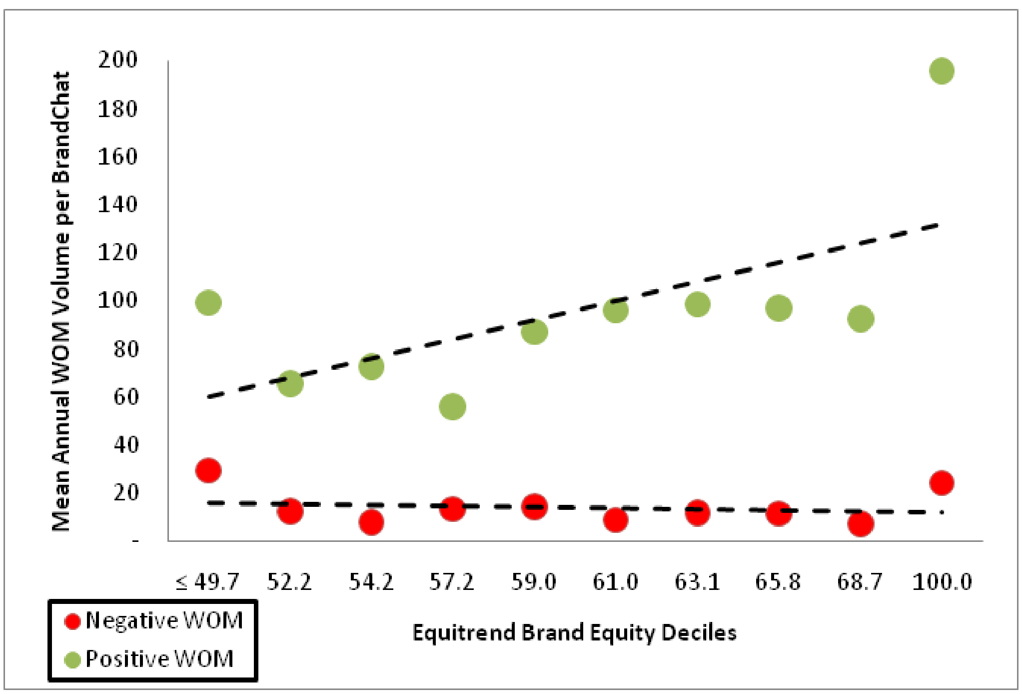


Figure 22: Average Brand Annual Positive and Negative WOM by Brand Equity Decile



Another insight from this study is that the strength of weak ties perspective may vary systematically depending on the overall strength of the brand. WOM communications between weak social ties for brands with lower brand equity were less capable of motivating additional information search, but weak-tie communications were essentially the same as strong-tie communications for motivating additional information search for stronger brands. In addition, intentions to seek information were overall higher for stronger brands. The strength of weak ties argument claims that weaker social ties serve an essential bridging function in the transmission of novel information across semi-closed strong-tie social networks. However, the strong ties still persist in being most effective at consistently influencing actual behavior. If stronger brands reap greater impact from weak-tie communications, such brands should be speedier at spreading new brand information across a wide swath of consumers. These results suggest that the acceleration and increase of cash flows, two mechanisms by which market-based assets link to brand performance (Srivastava et al. 1998), may be because strong brands are less reliant on established social relationships to facilitate effective WOM influence.

Implications for Marketing Management

The results of this investigation have numerous implications for marketers. First, they suggest that the overall strength of a brand has substantial implications about the likely impact of WOM marketing activities. The current study suggests that weak brands are in a disadvantageous position to leverage engineered WOM tactics, because an equivalent amount of WOM generation will have less overall impact on brand performance. These results suggest it may often be wiser for a marketer of relatively weak brands to invest in improving overall customer satisfaction and building equity through more traditional branding activities before utilizing engineered WOM tactics. These results do not suggest that weak brands can escape the

deleterious cycle of low brand equity (Keller and Lehmann 2006) by trying to directly influence WOM volume, as stronger brands can do so more efficiently and effectively. Another implication of this study is that brand managers should not focus only on monitoring the relative volume of positive and negative WOM with competing brands as a means to track how consumer advocacy/detraction is linked to brand outcomes.

Second, managers of weaker brands should place particular emphasis on generating WOM between stronger social ties. The potency of WOM between weak ties for weak brands for generating additional information search is not as strong. Conversely, managers of stronger brands should be less concerned about tailoring marketing efforts to generate WOM between strong or weak ties. Although it may be difficult for brands to craft their messaging in such a way to stimulate strong- or weak-tie WOM exclusively, there is some evidence that it can be crafted to some extent. For example, the advertising campaign for Old Spice men's body wash was initially successful at generating branded conversations between male and female couples (strong ties) before its runaway popularity turned the campaign into a conversation point between a much wider audience (weaker ties) (W+K 2010).

Limitations

Despite the unique insights from this inquiry, it is not without limitations. First, the previous limitations noted during Investigation 1 regarding the BrandChat measures certainly still apply. However, because the additional measures used in Investigation 2 are brand-level measures captured from independent sources, no further CMV threats are introduced. However, the reduced sample size and limited number of brands explored in this investigation raise the

question whether the insights derived from this investigation could apply to other brands excluded because of unavailable ACSI and brand equity measures. The omission of brands in Investigation 2 is not random; brands included are biased toward large, national, well-known brands. From this perspective, brands with lower equity may be truncated from the analysis. If anything, this suggests that the insights of the current study may be even more pronounced than if more less-known brands were included. This notion is merely speculative; further inquiries explicitly including more brands with much lower brand equity would need to be empirically evaluated to test it. Investigation 2's coverage of ACSI scores is more complete; that is, I was able to access the complete database of ACSI scores. However, again, the brands tended to be large, national brands and are also almost all owned by publicly traded firms. Thus, it is unclear whether the insights derived here regarding overall customer satisfaction apply to general levels of satisfaction for smaller, local enterprises (e.g., a local brew pub, an automotive repair store). Given that, in general, WOM is considered the lifeblood of such firms and geographically localized customer satisfaction sentiment may also play a role in the impact of individual WOM conversations, this limitation is a fruitful area for further inquiry. If anything, this localized version of general WOM sentiment may be even more potent for such brands. Furthermore, the current study focuses on general levels of brand strength as an aggregated snapshot across time. A future study could investigate whether changes in aggregate brand strength measures for a single brand over time are associated with changes in the impact in WOM activity. Such a study would provide additional insight into the question whether it is better for brand managers to focus first on generating WOM (though it may not be as effective given the current state of brand health) or cultivating brand equity/satisfaction (which would make WOM more impactful but

may not generate as much additional WOM as activities specifically focused on generating WOM).

Second, it is important to note that the current investigation directly links a particular WOM episode to immediate consumer response. The unique advantage of this approach is that it can connect a distinct WOM event to response (in contrast with other studies, in which this explicit stimuli response link is often merely assumed or implied). A limitation of this approach is that it does not account for how a consumer may be motivated to act on the basis of a progressive build-up of a variety of WOM episodes over time. For example, consider the case of the automotive category (in which a single WOM seemed particularly ineffective). Such results in the automotive industry do not mean that WOM in general is not an important factor influencing automotive purchase decisions; it merely shows that a single WOM episode is rarely enough to have an impact (Vakratsas and Ambler 1999). Much as advertising literature has suggested that it takes multiple exposures to an advertisement for it to have a meaningful impact on consumer response (wear-in), some product categories may require a substantial number of WOM episodes for WOM to be truly potent. To some extent, this limitation may be alleviated by controlling for the existing level of WOM volume about a brand (which potentially controls for brands that have more or less WOM buildup).

Third, the current study does not include measures of individual consumers' existing brand knowledge structures (e.g., mind-set variables). An important future extension of this inquiry would be to test whether general, environmental levels of brand satisfaction/brand equity interact with an individual consumer's satisfaction/brand equity perceptions of the brand. Such an investigation may be useful in explaining when WOM outcomes for a particular WOM recipient are particularly contradictory to expectations. Specifically, a relatively understudied

aspect of the WOM in marketing literature is reactance responses (Fitzsimons and Lehmann 2004): consumers purposefully acting in a contradictory way to received WOM about a brand. Perhaps consumers who harbor a different internal brand mind-set toward overall sentiment are more likely to engage in the relatively rare case of reactance as a response to WOM.

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PUBLICATIONS

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Baker, Andrew M., Ravi Parameswaran, and Balaji Rajagopalan (2008), “Drivers of Consumer Ratings in Online Recommender Systems: An Exploratory Analysis of Cross-Cultural Differences,” *American Marketing Association Winter Educator’s Conference*, San Diego, CA.

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