SOCIAL MEDIA EFFECTIVENESS

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ABSTRACT

Over the last decade, the advent of social media such as online product reviews (e.g., Amazon.com),blogs and other social networking sites (e.g., Facebook.com) has dramatically changed the way consumers obtain and exchange information about products. This dissertation investigates the impact of various types of social media on product performance and compares the effectiveness of social and traditional media under various conditions. Specifically, the first chapter performs a meta-analysis of consumer-generated WOM elasticity in social media to identify the factors that influence the impact of WOM on product sales and to assess the generalizability of the relationship. The second chapter examines how social media may influence product performance in different product contexts as compared with traditional media, which assists managers in making better media decisions. Taken together, this dissertation evaluates the progress in this field, and then takes a step further by applying past findings to understand how social media may perform at various stages in the product lifecycle.

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CHAPTER 1: A META-ANALYSIS OF CONSUMER GENERAGATED WORD-OF-MOUTH ELASTICITY IN SOCIAL MEDIA

Introduction

Interpersonal communication has been demonstrated to be one of the most influential sources in consumers' decision making in the literature (e.g., Brooks 1957; Katz and Lazarsfeld 1955). Consumers often recommend a new bank account, complain about a poor product, and even share a nightmare trip with their friends and colleagues. Most recently, with the advent of social media channels such as blogs, social networking sites (SNS henceforth) like Facebook, and third-party product review sites like Amazon.com, consumers are allowed to exchange information with their peers without any restrictions on time and location. This connects diverse individual consumers and extends interpersonal communication network from one’s small-scale direct personal contacts to the entire online world. In the marketing context, such interpersonal communications are known as word of mouth (WOM), that is, "informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers" (Westbrook 1987).

The impact of WOM on consumer purchase behavior has resulted in a number of studies that focus on quantifying the effect of WOM on product sales and firm performance. Among them, WOM includes many different conceptualizations and measures, for instance, oral WOM referrals from friends, colleagues or professional organizations (e.g., Nam, Manchanda, and Chintagunta 2010; Villanueva, Yoo, and Hanssens 2008), blogs (e.g., Gopinath, Chintagunta, and Venkataraman 2013; Onishi and Manchanda 2012), WOM referrals through social networking sites (e.g., Trusov, Bucklin, and Pauwels 2009), discussion forums (e.g., Gopinath

2011), and online consumer reviews (e.g., Chevalier and Mayzlin 2006; Chen, Wang, and Xie 2011). The various types of WOM and a broad range of platforms observed in extant research has led us to develop a parsimonious taxonomy of WOM to categorize these WOM papers. Hence, we identify two dimensions based on the nature of interpersonal communication: form of WOM transmission (whether it is public or private) and WOM audience size (whether it is a small network including only friends/acquaintances or a large network including unknown peer consumers). This gives rise to four main cells in the WOM taxonomy matrix (see Table 1):

In this study, we only focus on WOM classified in cells III and IV as there are insufficient papers about WOM classified in other cells. This is probably because public WOM is easier to access and measure than private WOM. In terms of WOM measurement, volume and valence are the metrics mostly utilized in the extant research to examine how effective WOM is in generating sales. In particular, volume refers to the total amount of WOM a certain product receives whereas valence refers to the degree of positive or negative WOM a product receives (i.e., average rating or number of positive/negative ratings).

A careful review of the previous research on WOM reveals the following tensions. First, there is no agreement on the best measure of WOM. Some studies use WOM volume (e.g., Trusov, Bucklin, and Pauwels 2009), other studies use WOM valence(e.g., Duan, Gu, and Whinston 2009) and yet other studies use both metrics (e.g., Liu 2006). Second, even when studies utilize comparable metrics, the results are mixed. For example, Liu (2006) and Duan, Gu, and Whinston (2008) find that the volume, and not valence, of consumer reviews is significantly associated with movie sales. However, Chintagunta, Gopinath, and Venkataraman (2010), using market-level data, find that it is the valence rather than volume that drives box office performance.

Similarly, Chevalier and Mayzlin (2006) find that better the consumer ratings, the greater sales. However, using a similar dataset from Amazon.com, Chen, Wu, and Yoon (2004) do not find any relationship between WOM valence and sales. Given the divergent results observed in existent WOM research, prior research (e.g., Kirca, Jayachandran, and Bearden 2005; Krasnikov and Jayachandran 2008) indicates that a meta-analysis of the WOM-sales relationship would be helpful in shedding light on contextual factors that can influence the effect of WOM metrics on performance and explain which metric of WOM is better to use under what conditions. To the best of our knowledge there is no meta-analysis of WOM effect on product sales.

We address this research void by conducting a meta-analysis of the effect of WOM on product sales. Following previous meta-analyses of marketing mix elements (e.g., Albers, Mantrala, and Sridhar 2010; Assmus, Farley, and Lehmann 1984; Sethuraman, Tellis, and Briesch 2011), we focus on the elasticity of WOM metrics on product sales. Specifically, WOM volume (valence) elasticity measures the percentage increase in product sales for one percentage increase in number of WOM messages (degree of positive or negative WOM). Our meta-analysis includes 281 WOM volume elasticities and 208 WOM valence elasticities reported in 40 studies.

We find the average WOM volume elasticity to be 0.256 and the average WOM valence elasticity to be 0.455. Furthermore, the WOM volume elasticities are higher (1) for durable products than for non-durable products, (2) for products with low trialability than for those with high trialability, (3) for privately consumed products than for publicly consumed products, (4) for the industry with a lower level of competition, (5) when estimated with reviews on specialized review sites as compared with those on general review sites, (6) when estimated with reviews on independent third-party review sites than on retailers' sites. In addition, WOM volume elasticities are affected significantly by temporal interval of dependent variable, omission of lagged dependent variable and omission of valence variable in the model. With respect to WOM valence, elasticities are greater (1) for low than high trialability products, (2) for products consumed in a private setting than a public setting, (3) for slow-growing industry, (4) for less competitive industry, (5) when estimated with reviews on independent third-party review sites than on retailers' sites. Moreover, WOM valence elasticities are influenced significantly by omission of distribution variable, estimation with negative ratings in the model, ordinary least square (OLS) estimation method, and omission of endogeneity in the response model. In term of the interaction effects between WOM valence and product/industry characteristics, our findings indicate that the interaction between product trialability and negative ratings are significant and positive. Also, the interactions between industry characteristics and valence measure are all significant and positive.

The paper is organized as follows. In section 2, we develop hypotheses regarding the effects of a series of factors that could influence WOM elasticities. Next, we describe data collection and the model used to test hypotheses. In section 4, we present results of our modeling analysis. Finally, we discuss our findings and identify avenues of future research.

Hypotheses

As summarized in Figure 1, our conceptual framework suggests that the differences in the effect of WOM metrics on sales can be explained by the contextual factors of product, industry, source characteristics, strategic actions of firms such as advertising, pricing and distribution, as well as measurement related factors such as model characteristics, data characteristics, omitted variables, and manuscript status. In this section, we develop hypotheses for main substantive variables and provide a detailed description of the expected relationship, rational and interpretation of the result for all of the variables included in this meta-analysis in Table 2.

Product Characteristics

Products differ in their durability, trialability and usage situation (public vs. private usage) (Berger and Schwartz 2011; Farley and Lehmann 1977; Rogers 1995). Moreover, these product characteristics influence a consumer's risk perceptions (psychological or financial) toward the product and therefore the scope of search undertaken to attenuate such risks. We next discuss how each of these individual product characteristics influence WOM volume and valence elasticities.

Product durability: durable versus non-durable. The products used in the WOM literature can be classified into durables and non-durables (Farley and Lehmann 1977). Durable goods are complex goods with large interpurchase intervals (e.g., automobiles and consumer electronics). On the other hand, non-durable goods (e.g., CDs, books and movies) are frequently purchased products with relatively short interpurchase intervals (Kim and Sullivan 1998). In addition, durable goods are generally more expensive than non-durables (Sethuraman and Tellis 1991). Due to these differences between durable and non-durable goods, durable goods are characterized by high perceived risk in relation to non-durable goods. As a result, consumers actively spend more time and effort conducting pre-purchase information searches from sources like WOM for durables than non-durables since wrong purchase decisions of durables generate high economic cost and force consumers to keep poor products for long periods of time (Laurent and Kapferer 1985). Therefore, we hypothesize the following:

H1a (H1b): WOM volume (valence) elasticities are higher for durable products than for non-durable products.

Product trialability: high versus low. Trialability measures the extent to which a product isavailable for initial trial prior to committing to its usage (Agarwal and Prasad 1997). Product trial allows consumers to gather product attribute information and more accurately gauge product quality (Wright and Lynch 1995). If a product has very low trialability, a peer consumer's product usage experience and knowledge can be used as proxy for trialability because it serves as a signal of quality (Bandura 1977; Gallaugher and Wang 2002), which in turn lowers the perceived risk in the purchase decision-making process. Therefore, we hypothesize:

H2a (H2b): WOM volume (valence) elasticities are lower for products with high trialability than for products with low trialability.

Observability of product consumption: public versus private. While making purchase decisions for a privately consumed product, individuals have had a very limited opportunity to learn from, and be affected by others through observation (Bikhchandani, Hirshleifer, and Welch 1992). However, as recent technological advances do allow consumers to gather information about these products through blogs, online forums and social networking sites, it becomes easier for consumers to evaluate whether the product matches their own preferences. Correspondingly, we posit that the persuasiveness of WOM recommendations may be greater for privately (versus publicly) consumed products since consumers have greater motivation to process information of products consumed in a private setting (Gatignon and Robertson 1985). Therefore, we propose the following hypothesis:

H3a (H3b): WOM volume (valence) elasticities are lower for publicly consumed products than for privately consumed products.

Industry Characteristics

While the product characteristics (above) address how brand-specific variables affect WOM elasticity, the industry characteristics capture environmental effects which can influence the effect of WOM on sales. Prior research has shown that industry growth and degree of competition are key environmental characteristics (Clemons, Gao, and Hitt 2006; Liu 2006).

Industry growth. Growth industries are associated with product changes, which in turn implies evolving customer preferences (Datta and Rajagopalan 1997; Gatignon and Xuereb 1997). It becomes more difficult for consumers to gather accurate information about product attributes and its fit with their preferences in such environments (Carpenter and Nakamoto 1989). Now prior research shows that consumers can easily and quickly learn from and tend to be affected by other consumers' usage experiences and opinions towards products through blogs, consumer reviews and so on when they make product judgments and purchase decisions (Godes et al. 2005). Thus, we posit that WOM exerts more influence on sales in the industry that exhibits higher growth because WOM can help individuals make more accurate predictions of the fit of the product with their preferences. Formally, we hypothesize that:

H4a (H4b): WOM volume (valence) elasticities are higher for the industry with greater growth.

Competition. Level of industry competition can be defined as the number of competitors coexisting in a market (Porter 1981). When the number of competitors in an industry increases, consumers have more product options to choose from. Research on consumer choice suggest that consumer's judgments are relative and are affected by the choice set (Lynch, Chakravarti, and Mitra 1991). Consumers tend to compare the alternatives in order to make final purchase decisions. However, in the reality, consumers often find they lack enough knowledge and time to make the optimal purchase decisions from dozens or even hundreds of competing products. The uncertainty about which alternative to choose results in increased product information search (Urbany, Dickson, and Wilkie 1989). Consequently, WOM becomes more effective for those consumers who face a few of alternatives as it is accessible for comparison among competing products without any time and location constraints. Therefore, we hypothesize the following:

H5a (H5b): WOM volume (valence) elasticities are higher for the industry with greater competition.

Source Characteristics

In the online environment, WOM arises from a vast number of unknown individuals. It is therefore the perceived source credibility of WOM that plays an important role on its persuasiveness, and in turn influences WOM elasticity. According to Kelman (1961), source credibility includes two major dimensions: expertise and trustworthiness. Specifically, expertise is the perceived ability of an information source to provide accurate information and trustworthiness is the perceived information source's motivation to make valid assertions without bias (McGuire 1969).

Expertise of WOM hosted platform: specialized versus general. In the WOM literature, the source of WOM includes a variety of review sites such as Epinions.com, Flixster.com, and so on. We chose to distinguish between specialized review sites with a narrow focus on a particular product category (e.g., Flixster.com for movies, Edmunds.com for cars) and general review sites that elicit customer reviews for a wide range of products (e.g., Amazon.com and Epinions.com) due to issue of WOM expertise. For instance, regarding car review sites, Car and Driver may attract more enthusiastic consumers who are experts on automobiles; whereas Epinions attracts mass consumers for car information (Chen, Fay, and Wang 2011). An expert on cars is likely to evaluate cars on a larger number of dimensions than a novice and she is also more likely to tell the difference between the handling characteristics of different competing models (Moorthy, Ratchford, and Talukdar 1997). Thus it is not surprising that people use expertise to evaluate the credibility of unfamiliar information (Eastin 2001). Thus, we hypothesize the following:

H6a (H6b): WOM volume (valence) elasticities estimated with reviews on specialized review sites are higher than those estimated with reviews on general review sites.

Trustworthiness of WOM hosted platform: independent third-party review sites versus retailers' sites. The platforms that host WOM information can be categorized into independent third-party review sites (e.g., Epinions.com) and retailers' sites (e.g., Amazon.com). Previous literature suggests that retailers may have an incentive to manipulate consumer reviews on their sites in order to generate more sales (Awad and Etzion 2006; Gu, Park, and Konaana 2011). In contrast, independent third-party review websites provide more objective information and are not subject to censoring concerns, thus being perceived as more unbiased and trustful sources and having greater influence on consumer decisions (Senecal and Nantel 2004). Therefore, we hypothesize the following:

H7a (H7b): WOM volume (valence) elasticities estimated with reviews on independent third-party review sites are higher than those estimated with reviews on retailers' sites.

Data and Methodology

To create our database, we conducted a thorough search for studies that report WOM volume and valence elasticity estimates (or regression coefficients) in social media. Specifically, in addition to studies that report WOM elasticities directly (e.g., Trusov, Bucklin, and Pauwels 2009), we applied different methods for various models and functional forms to transform regression coefficients into elasticities for those that do not report elasticities as a measure of WOM effectiveness (e.g., Duan, Gu, and Whiston2008).The search procedure was performed as follows. First, we conducted an issue-by-issue search of relevant publications from major journals in marketing, management and information systems that typically publish studies pertaining to WOM (specifically Journal of Marketing, Journal of Marketing Research, Marketing Science, Management Science, Journal of the Academy of Marketing Science, Information Systems Research, Decision Support Systems, Electronic Commerce Research and Applications, Journal of Interactive Marketing, Journal of Retailing, International Journal of Research in Marketing, Journal of Advertising, Journal of Advertising Research, Marketing Letters). Second, we used keyword searches (e.g., "online WOM", "social media", "online reviews") in several electronic databases such as ABI/INFORM, Business Source Premier, ScienceDirect, and Google Scholar to identify articles that pertinent to our study. Third, we searched the Web for working papers (for instance, Social Science Citation Index, Social Science Research Network, Marketing Science Institute, key authors' webpages). Fourth, we conducted a search for dissertations in ProQuest Dissertation and Theses database. Fifth, we reviewed the references lists in all of the previously obtained articles. Finally, we contacted key authors in this field to request unpublished or working papers.

Articles included in the database were based on two criteria. First, consistent with the scope of previous meta-analyses of marketing instruments (e.g., Assmus, Farley, and Lehmann 1984; Bijmolt, van Heerde, and Pieters 2005; Sethuraman, Tellis, and Briesch 2011), we restrict our analysis to the elasticities estimated from econometric models. Thus, we exclude studies using experimental and judgmental data such as purchase intention or preferences. Second, we only consider studies in which elasticities are unambiguously reported or derivable from the estimated coefficients in the regression. However, when we could not calculate the elasticities we made every effort to contact the authors to get the information necessary to calculate elasticities.

Based on our screening criteria, we identified 40 empirical studies, providing 282 WOM volume elasticities and 208 WOM valence elasticities. We dropped one WOM volume elasticity from the dataset after conducting outlier analysis. Thus, our final research database consists of 281 WOM volume elasticities and 208 valence elasticities reported in 40 studies. The number of studies included (40) is consistent with several other meta-analyses of different elements of marketing mix such as Assmus, Farley, and Lehmann (1984: 16 studies of advertising elasticity) and Tellis (1988: 42 studies of price elasticity).The minimum and maximum number of WOM volume (valence) elasticities reported in a study is 1 (1) and 46 (36) respectively.

The coding scheme used in our research is shown in Table 3. Unlike traditional meta-analysis that relies soles on data from studies in the literature, we go beyond and collect more primary data on each study in this meta-analysis. Following the coding method in Chandy and Tellis (2000) and Srinivasan, Lilien, and Rangaswamy (2006), we used two expert coders to independently code the product and source characteristics identified in our conceptual framework. Agreement between the two coders was greater than 85%, and the remaining disagreement was resolved by a third researcher. As for the industry characteristics, we used the historical method to collect data on industry growth and number of competitors. Regarding other influencing factors such as firm actions, data characteristics, omitted variables, model characteristics and manuscript status, we obtained these data directly from the individual study. Tables 4 shows the summary statistics.

Estimation Model and Procedure

Our analysis proceeds in two stages. First, we perform a univariate analysis to obtain estimates of the mean WOM volume and valence elasticities. We also analyze the distribution of WOM volume and valence elasticities. Second, we estimate the impact of the factors described above on WOM volume and valence elasticities. In the context of quantitative meta-analysis, data have a nested or hierarchical structure (i.e., subjects nested within studies) (Denson and Seltzer 2011), making traditional regression analyses such as OLS inappropriate because nested data structures may lead to heteroskedasticity in the errors (Krasnikov and Jayachandran 2008).Thus, to account for within-study error correlations between WOM elasticities, we perform the meta-analysis with hierarchical linear modeling (HLM), as suggested by Bijmolt and Pieters (2001). We estimate the models using the maximum likelihood method, which is the most common estimation method in multilevel modeling since “it is generally robust, and produces estimates that are asymptotically efficient and consistent” (Hox 2002; Singer and Willet 2003).The estimated model is as follows:

$$Y_{ij} = \beta X_{ij} + z_j + e_{ij} \tag{1.1}$$

where Y_{ij} is the ith WOM volume (or valence) elasticity from study j, β is the parameter estimate of the influencing factors, X_{ij} are a series of factors that influence the WOM volume (or valence) elasticity, z_j is the study-level residual error term, and e_{ij} is the measurement-level residual error term.

Robustness Checks

Before estimating a HLM, we conducted several checks to ensure the robustness of this meta-analysis. First, we examined the correlations among the potential factors in both volume and valence models. We identified "product durability" with posing potential problems of collinearity in the valence model, and thus excluded this factor and retained others in the final valence model. Then, we found that 13 of 210 correlations in the volume model and 12 of 231 correlations in the valence model (with potential interaction effects) were greater than 0.5. Among them, only 2 correlations in each model were greater than 0.7. Next, we performed sensitivity analyses by omitting each of the factors with at least one correlation greater than 0.5 one at the time as proposed in previous meta-analyses (e.g., Bijmolt, van Heerde, and Pieters2005). The results were unchanged as compared with our original model, which indicates multicollinearity is sufficiently low. Finally, the variance inflation factors (5.03 in the volume model and 9.9 in the valence model) confirm that multicollinearity does not unduly influence the findings.

Second, we considered various plausible interaction effects among product characteristics, industry characteristics, source characteristics, and WOM metrics in both volume and valence models. However, due to extremely multicollinearity caused by adding certain interaction effects, we retained interactions between WOM valence measure and product/industry characteristics in the final valence model whereas we did not include any interaction effects in the final volume model.

Third, we performed a residual analysis of errors to test if the assumptions of HLM are satisfied (Hox 2002; Singer and Willett 2003). The residual plot did not show significant violations.

Results

Univariate Analysis of WOM Elasticity

Figures 2 and 3 present the frequency distribution of the WOM volume and valence elasticity estimates respectively. There are 281 (208) WOM volume (valence) elasticities with magnitudes ranging from -1.44 (-5.86) to 2.98 (7.73). The overall mean WOM volume and valence elasticities in our meta-analysis are 0.256 (median = 0.134, standard deviation = 0.505) and 0.455 (median = 0.135, standard deviation = 1.65). In the existing WOM literature, online consumer reviews can influence product sales through awareness effects of volume or persuasive effects of valence, or both (Duan, Gu, and Whinston 2008; Liu 2006). As the results show, the mean of WOM valence elasticities is much higher than that of WOM volume elasticities, which highlights the importance of the persuasiveness role as compared with the informative role of WOM in changing consumer behavior and market outcome.

Effects of Influencing Factors

Effects of substantial factors. The results of the HLM regression for the meta-analysis are shown in Table 5. As for the effect of product characteristics, consistent with our hypothesis H1a, we find WOM volume elasticities (β=0.527, $p<0.05$) are higher for durables than for non-durables. We also find both WOM volume and valence elasticities (β= -0.456, $p<0.05$; β= -2.64, $p<0.001$) are lower for products with low trialability as compared to those with high trialability, which confirms hypotheses H2a and H2b. In addition, our results show that for public (versus private) products, WOM volume elasticities (β=-0.444, $p<0.05$) are lower, similar to the valence elasticities (β= -2.159, $p<0.05$). This supports hypotheses H3 (H3a and H3b).

Regarding the influence of industry characteristics on WOM effect, we find that the higher the industry growth, the lower the WOM valence elasticities (β= -0.009, $p<0.05$), which contradicts to H4b. Perhaps, in the industry with rapid product changes, product reviews provided by those early adopters (also early reviewers) may not be an unbiased indication of unobserved quality due to self-selection bias, thus discounting WOM effectiveness. Alternatively, rapid changes in products may make even WOM obsolete in making purchase decisions. However, we do not find significant results with WOM volume elasticities. Surprisingly, the results also indicate that both WOM volume and valence elasticities (β= -0.001, $p<0.05$; β= -0.006, $p<0.001$) are lower with a greater level of competition, opposite to the hypotheses H5a and H5b.A possible explanation for this finding is that when a number of competitors co-exist in an industry, consumer heterogeneity in preferences may result in diverse endorsements for different brands, which makes peer consumers uneasy to make purchase decisions based on contradictory information.

With the respect to the effect of source characteristics, we find that WOM volume elasticities are greater by 0.274 ($p<0.1$) when estimated with reviews on specialized review sites than when estimated with reviews on general review sites, which supports H6a. But this does not apply to valence elasticities probably because comments on the specialized sites may be perceived as biased due to strong preference of expert reviewers who are either fan or hater of a certain product. Moreover, consistent with H7a and H7b, we find that WOM volume and valence elasticities ($\beta= 0.649$, $p<0.001$; $\beta= 2.729$, $p<0.001$).estimated with reviews on independent third-party review sites (e.g., Epinions.com) appear to be higher than those estimated with reviews on retailers' sites (e.g., Amazon.com).

Effects of other factors. In terms of firm actions, we do not find any effect of the omission of advertising and price from the response models on WOM volume and valence elasticity estimates. However, we do find the omission of distribution from the response models has a statistically significant positive effect on WOM valence elasticities ($\beta= 1.476$, $p<0.05$) whereas it has no impact on WOM volume elasticities.

As for data characteristics, our results indicate that the temporal interval of the dependent variable affects WOM volume elasticities but not valence elasticities. Specifically, WOM volume elasticity estimates increase by 0.461 ($p<0.05$) when estimated with daily instead of weekly or monthly sales data. In addition, the measure of WOM volume, that is, whether it is cumulative or single period, does not have any effect on volume elasticity estimates. We also find the measure of WOM valence affects valence elasticities differently in that negative ratings produce much lower valence elasticities ($\beta = -4.852$, $p<0.001$) than average ratings though positive ratings do not seem to influence the estimates. Interestingly, WOM valence value does not have an effect on valence elasticities. A potential explanation could be ratings may be perceived as relatively ambiguous as most of product categories in the existing research are non-durable products like movies, books and so on.

The results also show that the omission of lagged dependent variable and valence from response models for WOM volume leads to an increase and decrease respectively in WOM volume elasticities ($\beta = 0.352$, $p<0.05$; $\beta = -0.418$, $p<0.05$). However, we do not find the same results with WOM valence elasticities.

With regards to the model characteristics, we do not find any significant effect of different functional forms on WOM volume and valence elasticity estimates. However, we find that response models estimated with OLS tend to produce higher WOM valence elasticities ($\beta = 1.552$, $p<0.05$) than other estimation methods. This is not the case for volume elasticities. In addition, the results indicate that failing to explicitly account for endogeneity induces a negative bias in WOM valence elasticity estimates ($\beta = -0.844$, $p<0.05$), nevertheless, it does not affect volume elasticity estimates. Furthermore, the results show that the omission of heterogeneity does not bias both WOM volume and valence elasticities. Also, no publication biases were found in WOM volume and valence elasticity estimates.

Finally, our results from the WOM valence model indicate that the interaction between product characteristics (i.e., trialability and observability of consumption) and positive valence measure is non-significant. However, the interaction between product trialability and WOM negative valence measure is significantly positive ($\beta = 2.559$, $p<0.05$) while the interaction between observability of product consumption and negative valence measure is not significant. Additionally, we also find significant positive interaction effects between industry growth/competition and positive/negative valence measure ($\beta = 0.015$, $p<0.05$; $\beta = 0.015$, $p<0.1$; $\beta = 0.018$, $p<0.001$; $\beta = 0.034$, $p<0.001$).

Discussion and Future Research

Discussion

The findings in our study indicate that WOM volume is more effective in driving sales for durable products than non-durable products possibly because consumers engage in extensive pre-purchase information searches for durables (as compared to non-durables) to reduce perceived psychological and financial risk while purchasing. In addition, the findings show that compared to low trialability products, products with high trialability induce lower WOM volume and valence elasticities possibly since peer consumers' product experience plays an important role in serving as quality signal for low trialability products. Interestingly, our findings also indicate that both WOM volume and valence are less effective in generating product sales for publicly than privately consumed products. This confirms our expectation that consumers may have a greater level of motivation to process information towards private products than public products, which comes from unobservable consumption experience of peer consumers.

As for industry characteristics, we find that a greater level of industry growth produces lower WOM valence elasticities, contradictory to our expectation, but has no effect on volume elasticities. A possible explanation for this surprising result is in industries with rapid product changes, WOM valence provided by those early adopters (also early reviewers) may not be an unbiased indication of unobserved quality due to self-selection bias or ‘fertilization’ of WOM by firms (Godes and Mayzlin 2009), thereby discounting WOM effectiveness. In contrast, WOM valence may be perceived as more "reliable" by consumers in a slow-growing industry and hence, have a greater impact on product sales. However, the effect of WOM volume on product sales may not depend on the level of industry growth probably because as a signal of popularity, volume is perceived as more product-specific in different industries. Furthermore, the results also indicate that greater competition in an industry, the lower the WOM volume and valence elasticities are, again contrary to our expectation. This may be explained by the fact that when a number of competitors co-exist in an industry, consumer heterogeneity in preferences may results in diverse endorsement for different brands, which makes peer consumers uneasy to make purchase decisions with such crowded information.

With regard to source characteristics, our findings show that WOM source expertise increases volume elasticities but it does not have an impact on valence elasticities. This implies that the review informativeness is high for those specialized review sites as there are probably sufficient product expert users' reviews, which enable individuals to learn product benefits and how the product matches their differing usage conditions easily. However, the ratings from those expert consumers may not be perceived as credible as they are expected, probably because those ratings are very subjective to expert users' personal preferences. In other words, the expert consumer could be either a fan or a hater of a particular product she knows very well. Moreover, the results also indicate that WOM source trustworthiness increases both volume and valence elasticities.

Thus, WOM from independent third-party review sites appears to be more effective in influencing consumer purchase decisions than that from retailers' sites. This finding is important since it demonstrates that not all social media and WOM are created equally.

Additionally, we do not find any biases caused by omitting advertising from the estimation equation, for either WOM volume or valence elasticity estimate. A possible explanation is that both positive and negative correlations between advertising and WOM exist in different studies in our database, so that the complementary and substitutable effect between these two constructs may be offset. Similarly, the inclusion of price does not impact WOM volume and valence elasticity estimates, which may be because, for the products in our study, prices tend to stay fixed over a long time period. In contrast, our results also indicate that the absence of a distribution variable from the response model positively bias the obtained valence elasticities, consistent to our expectation. However, it does not bias the volume elasticities, perhaps because for certain products in our study, a lower level of distribution also stimulate consumers' curiosity and WOM, which balances out the positive correlation between these two variables.

Our findings also indicate that WOM volume elasticity estimates are greater when the dependent variable are less aggregate (daily) than more aggregate (weekly or monthly), which is consistent to our expectation. Nevertheless, valence elasticity estimates are not affected by the temporal interval of the dependent variable. In addition, the measure of WOM volume (whether accumulative or single period) does not bias volume elasticities. One potential reason is that WOM also generate strong carryover effect (e.g., Liu 2006; Trusov, Bucklin, and Pauwels2009), which may negate the recency effect on consumer decision-making. Interestingly, regarding the measure of WOM valence, we find that using negative ratings in the model produces lower valence elasticities as compared to using mean valence ratings whereas using positive ratings in the model does not bias the valence elasticities. This finding could be explained by the product categories in our dataset. As many of the extant studies concentrate on non-durable products including books, CDs, movies and online games etc., personal tastes play a large role in these product categories. Thus, the favorable ratings for these products may be viewed as relatively ambiguous, which could prompt more uncertainty in the evaluation (Wyer 1974). This finding implies that not all reviews are evaluated equally. In terms of the WOM valence value, the finding shows it does not have an effect on valence elasticities. A further analysis of the reported average valence ratings in our study illustrates that the variation in the valence of reviews is so limited that it does not impact on elasticity estimates.

With respect to the omitted variables, our analysis suggests that the omission of lag dependent variable from the response models positively biases the WOM volume elasticity estimates but not the valence elasticity estimates, probably because valence ratings could be either positively or negatively correlated with lagged sales. Our results also show that the omission of valence from the response models negatively biases the WOM volume elasticity estimates. However, WOM valence elasticity estimates are not influenced by whether the variable of volume is included in the model or not.

Furthermore, no significant differences in WOM volume and valence elasticity estimates were found across different functional forms, a result consistent with previous meta-analysis findings. As Tellis (1988) discusses, an appropriate functional form is an empirical issue, and our findings confirm that there is no single “best” model for WOM modeling. Our results also indicate that volume elasticities are not sensitive to estimation methods, although models estimated by OLS are associated with higher WOM valence elasticities. No satisfactory explanation for this difference is apparent. We find that the omission of endogeneity induces a negative bias in the WOM valence elasticity estimates but not in the volume elasticity estimates, thereby highlighting the importance of explicitly accounting for potential endogeneity in WOM response models. We also find that both volume and valence elasticity estimates are not affected when response models do not account for heterogeneity. Additionally, the insignificance of publication bias ensures the robustness of our meta-analysis findings.

Finally, our findings from the WOM valence model indicate that for the interaction between product characteristics and valence measure, only the interaction between product trialability and negative ratings are significant and positive, consistent to our expectation. Other insignificant results imply that extreme valence measure may not be more informative than average ratings for products with different characteristics included in our study. However, the interactions between industry characteristics and valence measure are all significant and positive, which confirm our expectations.

Implications and Future Research

Implications. Our findings provide several implications for researchers and managers. First, the finding that WOM volume is more effective in driving sales for durables than non-durables directs researchers to make more efforts on investigating WOM-sales effect on more types of durables as most of the extant studies concentrate on durables limited to cars and consumer electronics and non-durable products including books, CDs, movies and online games etc. Second, the results that both WOM volume and valence affect privately consumed product sales at a greater level as compared with publicly consumed product sale suggest that managers should emphasize on social media application when they advertise products like night bed mattress, toothbrushes and so on. Third, WOM valence elasticities are found to be larger for slow-growing industries and less competitive industries, which suggests that managers should carefully deal with consumers' criticism and complaints in a timely fashion especially in these industries. Fourth, our finding that WOM valence elasticity is not significantly different depending on whether reviews come from general or specialized social media platforms suggests that managers not be too bothered by the negative reviews from expert consumers on certain specialized review sites. Fifth, we find that WOM from independent third-party review sites generates higher elasticities than that from retailer's review sites. One implication is that not all social media platforms are created equally, so that managers should strategically choose the right media for marketing their products. Sixth, from a modeling perspective, the result of positive bias induced by the omission of distribution on valence elasticity underscores the need to include as many relevant covariates (e.g., marketing mix variables) when available to researchers. Seventh, the finding that valence elasticity differs significantly according to which measure is used (positive/negative or average) implies that not all WOM are evaluated equally. Thus, researchers must distinguish what measure they are studying and make corresponding conclusions. Eighth, we find that functional forms such as OLS or others may produce different valence elasticities, which leads researchers to understand appropriate econometric approach to solve problems. Ninth, the significance of the omission of endogeneity in the valence model emphasizes that endogeneity is a serious concern that must be addressed in any such model. Lastly, we find that the interactions between valence measure and product/industry characteristics induce positive bias in valence elasticities. These results suggest that researchers should consider the settings (e.g., product category and industry) and WOM measure together for their empirical analysis and generalization.

Future research. Based on our meta-analysis results, we now identify avenues of future research. First, the interaction of WOM and marketing mix variables needs to be examined by researchers. For example, our results show that consumers are more responsive to WOM for durables than non-durables. While this finding is consistent with the idea that consumers engage in pre-purchase search, we do not directly observe consumer information search behavior. Consumers may browse and gather product information without immediate purchase goals (i.e., ongoing search) and end up with an impulse purchase, especially for those nondurable products like cosmetics and CDs. So researchers could investigate how consumer information search motive (pre-purchase vs. ongoing search) affects the difference of WOM effectiveness between durables and non-durables. Similarly, much research in this area including distribution simply examines the level but not the process of distribution. In fact, product can be introduced to the market simultaneously or sequentially (Lehmann and Weinberg 2000). Future research needs to examine which types of social media are more effective for sequentially (or simultaneously) distributed products.

Second, the taxonomy generated seeks to classify research on WOM into a limited number of categories of WOM and this meta-analysis focuses only on one category of research. Future research could provide insights on differentiation and comparison of a variety of WOM effects. For instance, for large network size, how does the effect of private WOM differ from that of public WOM? In addition, for private WOM, how many times of WOM effectiveness in large network size as compared with small network size? Furthermore, how do product and industry characteristics influence the differential effects of private WOM in a small network size and public WOM in a large network size?

Third, most of the empirical studies in our meta-analysis use WOM data from United States. As WOM transmission is relevant to cultural factors such as individualist/collectivist and high/low uncertain avoidance, its effects may be significantly different in different countries. Thus, researchers should investigate various types of WOM in other countries for comparison and generalization of WOM effectiveness.

Fourth, similar to source characteristics, the characteristics of the message recipient may affect the impact of the message on sales. In this meta-analysis, we differentiate between generalized and specialized review sites according to the level of WOM expertise. Researchers may further examine how characteristics of the source of message interact with characteristics of the recipient of message to influence product sales. For example, consumers can be classified into expert and novice consumers. The potential research questions could be whether generalized and specialized review sites affect expert and novice consumers' purchase decisions in a different way.

Conclusion

The objective of this study was to draw insights from the existing literature on consumer generated WOM, to help understand the factors that influence WOM elasticities, and, based on the results, to provide implications for researchers and managers and further research avenues in this evolving field. We collected a large number of WOM volume elasticities and valence elasticities reported in 40 studies and identified a series of factors that influence these elasticities. The average WOM volume (valence) elasticity across the 281 (208) observations is 0.256 (0.455). Consequently, we find that product durability, product trialability, observability of product consumption, industry competition level, industry growth, expertise and trustworthiness of WOM source, temporal interval of dependent variable, omission of lagged dependent variable and omission of valence significantly affect the WOM volume elasticity estimates. We also find that product trialability, observability of product consumption, industry growth and competition, trustworthiness of WOM source, omission of distribution, valence measure, estimation method and endogeneity significantly influence the WOM valence elasticity estimates. These findings, to some extent, help us understand whether and how social media works. Based on our meta-analysis, we discuss implications for researchers and managers, and opportunities for future research.

The limitations of this study provide insights into avenues for future research. First, as with all meta-analyses, although we have tried to conduct a comprehensive review of the existing literature, we may have overlooked some published or unpublished studies about WOM elasticities, especially because this is a rapidly evolving field. Second, we use WOM volume and valence elasticities as dependent variables since these are the most popular measures in the literature. Thus, WOM dispersion, variance and other important measures have not been examined due to restriction of sample size. Third, the influencing factors we identified in our meta-analysis are limited by the variables included in the original studies. Future research could provide more insights upon further exploration.

Word-of-mouth is a powerful marketing technique that has the potential to affect every facet of business. However, the field is still trying to understand its various nuances and a snapshot view such as this research that provides both a summary of extant research as well as directions forward should help in driving the field forward.

CHAPTER 2: THE IMPACT OF SOCIAL MEDIA ON NEW PRODUCT SALES, AND CUSTOMER ACQUISITION AND RETENTION FOR ESTABLISHED PRODUCTS

Introduction

The Internet with Twitter, Facebook, YouTube or MySpace has completely changed how we perceive and understand our environment.

----– Michael Lynton, 2009, CEO & Chairman, Sony Pictures Entertainment

Over the last decade, the advent of social media such as blogs, online consumer reviews, Facebook and other social networking sites has dramatically changed the way consumers obtain and exchange information about products (Hennig-Thurau, et al. 2010). Social media enables consumers to share their product knowledge and experience with others anywhere and anytime, thus exerting a significant influence on consumers' purchase behavior. This provides companies tremendous opportunities to better engage with consumers.

This explosion of social media and other technologies is threatening several established business models (Hennig-Thurau, et al. 2010). Printed newspapers and magazines are facing a major crisis as readers migrate to the Internet (Edgecliffe-Johnson 2008). The global advertising expenditures on newspapers and magazines are expected to drop by 2% between 2010 and 2013, according to the Advertising Expenditure Forecast. In contrast, due to technological improvements such as high-definition TV (HDTV) and 3D TV technology, bigger and higher-quality pictures in addition to more channels has resulted in people watching more TV. As a consequence, the share of TV advertising has increased from 37.1% in 2005 to 40.7% in 2010, and is expected to grow to 41.8% in 2013 (ZenithOptimedia 2010). So “traditional media are not disappearing” (Winer 2009), but instead they substitute or complement social media. These developments have lead major marketers to shift their focus on different media to reach customers and reallocate their budgets into “alternative” media, which results in a new media landscape. Thus, it is important to understand how to use social media, how social media interacts with traditional media, and how social media influences a range of outcomes such as customer acquisition and retention (Libai, et al. 2010).

Recent and past research has studied the effect of social media on sales of new products including TV shows (e.g., Godes and Mayzlin 2004), movies (e.g., Liu 2006; Gopinath, Chintagunta, and Venkataraman 2013; Onish and Manchanda 2012), music (e.g., Dhar and Chang 2009), and cellular phone service (e.g., Onish and Manchanda 2012) as well as established products such as books (e.g., Chevalier and Mayzlin 2006), smart phones (e.g., Tirunillai and Tellis 2012) and microloans (e.g., Stephen and Galak 2012). However, the effect of social media relative to that of traditional media has not yet been well-examined for new and established products.

Our research aims to investigate the differing roles of traditional advertising vehicles (e.g., television, radio, newspaper and so forth) and social media platforms (such as blogs and online consumer reviews) over the lifecycle of a product. More specifically, our research aims to answer the following questions:(1) what is the effect of social media relative to that of traditional media on new product sales?, (2) for established products, how does the impact of social media and traditional media advertising differ for customer acquisition and customer retention?, and (3) does the interaction effect between social and traditional media differ in new and established product contexts?

We develop a conceptual framework and method to compare the impact of traditional and social media on different marketing outcomes, which assists managers in making better media decision. We form hypotheses and test them using secondary data from the automobile industry. This research can lead to insights into how the different types of media fulfill firm advertising objectives and how to take advantage of social media to improve firm performance under distinct contexts and conditions.

The contributions of this research are as follows. First, to the best of our knowledge, this is the only study to compare the impact of social and traditional media on a variety of product performance metrics (i.e., sales, customer acquisition and retention) for new and established products respectively, which can help managers to choose appropriate media strategies under different marketing contexts. Second, this study integrates and examines the within-media synergy of social and traditional media as well as the cross-media synergy between these two types of media, which could help managers to apply the proposed model and estimation method to estimate both social and traditional media effects as well as how the various media interact with each other using market data. Third, this study also demonstrates that the cross-media synergy between social and traditional media could be different for different product contexts in this new media landscape. Our findings challenge the traditional view that media synergy is always positive by incorporating the new forms of media. Through understanding the synergy effect of social and traditional media for new and established products, managers could strategically allocate resource in today's multimedia world.

The rest of this paper is organized as follows. We begin by reviewing literature on the advertising effectiveness of traditional media, as well as the distinctions of social media and the impact of social media on marketing performance. Then we provide hypotheses about the impact of social media relative to that of traditional media for new and established products respectively based on existing theories from the advertising, communication and consumer psychology literatures. Next, we discuss the methodology and data source that we apply to test these hypotheses. Finally, we present the results, and then discuss their implications for marketing strategies.

Literature Review

Advertising Effectiveness of Traditional Media

In the literature, a number of studies have been carried out by researchers about the advertising elasticity of traditional media for products over time (e.g., Hu, Lodish, and Krieger 2007; Lodish et al. 1995a; Parsons 1975). Most of these studies use real market data from research firms/advertisers or data generated from market experiments. In addition, a variety of reviews and comprehensive meta-analyses have been conducted to summarize the findings about advertising elasticity from numerous original econometric models over a long time span (e.g., Assmus, Farley, and Lehmann 1984; Sethuraman and Tellis 1991; Sethuraman, Tellis, and Briesch 2010; Vakratsas and Ambler 1999). (See Table 6 for empirical generalizations about advertising elasticity of traditional media generated from these studies). The variability in advertising elasticities implies that it is important to carefully think about choosing which products to advertise at what point of time, optimally choosing media that fulfills the advertising objective, and investing in high-quality creative (Hanssens 2009).

Characteristics of Social Media

In contrast to one way communication used in traditional marketing, marketing becomes a two way communication with the advent of social media (Eley and Tilley 2009). Social media can take on many different forms including blogs, microblogs, product reviews and online discussion forums etc. The information created and exchanged in the social media by non-media professionals is known as user generated content (UGC) (Kaplan and Haenlein 2010).Social media have had a profound effect on how millions of consumers purchase products, view brands and interact with others. The increasing influence of social media provides companies tremendous opportunities to better engage with consumers. For instance, Coca-Cola is shifting its digital focus towards social media from traditional campaign sites. The company positions its official Facebook and YouTube pages as the lead online channels for its international marketing activities on Coke Zero and Fanta brands. So far, Coca-Cola has the second most popular page on Facebook with more than 5 million fans (Sviokla 2010). Ford also used social media successfully to launch its Explorer. The reveal of the 2011 Ford Explorer on Facebook caused a 104% increase in the number of people going to Ford Explorer pages online. Furthermore, Ford achieved a greater market share of SUV shoppers across 13 shopping and enthusiast websites (Greenberg 2010).

These examples imply that social media can play several roles in transforming the relationship between businesses and consumers. First, social media allows a company to directly engage their consumers in the creative process, which leads customers to become active participants instead of passive recipients (Thackeray et al. 2008). Second, social media is perceived by consumers as a more trustworthy source of information about products and services than company-sponsored ads in traditional media (Foux 2006), partly because the content, timing, and frequency of consumers' communications on social media are generally out of managers' direct control (Mangold and Faulds 2009). Third, social media enhances the power of WOM marketing by increasing the speed at which customers share feedback, comments and reviews (Thackeray et al. 2008; Swartz 2009). Fourth, social media provides a cost efficient way for a company to reach customers (Dellarocas 2003; Swartz 2009). It is relatively inexpensive and accessible to publish or access information.

The Impact of Social Media on Product Performance

In response to the importance of social media, a growing body of literature examines the impact of social media on product performance. Among them, several studies investigate the effect of social media for new products. For example, Godes and Mayzlin (2004) use online conversations to evaluate the impact of WOM volume and dispersion on new TV shows' ratings and find that WOM dispersion is positively related to while volume is not consistently associated with the TV shows' future ratings. Liu (2006) investigates the relationship between online movie reviews and box office sales based on weekly data regressions. The results show that the online message volume is significantly correlated with movie sales even though its valence is not associated to sales. Dhar and Chang (2009) explore the impact of online chatter on music sales and find higher number of blog posts corresponds to higher future sales. Using data on new product launches of movies and cellular phone service in Japan, Onishi and Manchanda (2012) find that blog volume and valence are predictive of market outcomes and the effects of TV advertising and blogging act synergistically. Additionally, blogging is spurred by pre-launch TV advertising but this effect declines post-launch. Moreover, Gopinath, Chintagunta, and Venkataraman (2013) use movie data to explore the differences across geographic markets in response to pre- and post-release blog volume, blog valence and advertising. Their findings reveal that demographic factors such as gender, income, race and age all drive the across-market response differences to these metrics. And the release day movie performance is influenced by post-release blog volume and advertising while post-release movie performance is affected by post-release blog valence and advertising.

Furthermore, there have been a few studies focusing on the impact of WOM on product performance for established products. For instance, Chevalier and Mayzlin (2006) examine the effect of user reviews on relative sales of books at two public websites (*Amazon.com* and *BN.com*). Their findings suggest that greater number of favorable book reviews at one site is related to higher sales of a book at that site relative to the other site. However, an incremental positive review is less impactful in increasing book sales than an incremental negative review is in decreasing sales. Tirunillai and Tellis (2012) aggregate data across six product categories and fifteen firms over a four year period to assess the short-term and long-term relationship between UGC and stock market performance. The findings reveal that chatter (volume) has the strongest relationship with stock returns and trading volume. With regard to valence, negative UGC has a strong effect while positive UGC does not have any effect on returns. Stephen and Galak (2012) examine the effects of traditional and social earned media on sales through a dataset of 14 months of daily performance and media activity for a microfinance website. The authors confirm that both traditional and social earned media have strong effects on sales and social earned media has a greater sales elasticity than traditional earned media. Moreover, the per-event sales impact of traditional earned media activity is larger than for social earned media.

Although the impact of social media has received the attention of researchers, little is known about this impact on products over time. While the advertising effectiveness of traditional media for new and established products has been well-examined in the literature, with the popularity and distinction of social media it is important to provide insights into how social media can influence different marketing outcomes such as sales for new products or customer acquisition/retention for established products, as compared to traditional media, and whether social and traditional media have differential interaction effects in new and established product contexts. To address these issues, we next develop a conceptual framework and form hypotheses regarding these research questions.

Conceptual Framework and Hypotheses

It is commonly recognized that advertising can have a variety of effects on consumers' thoughts, attitudes and purchase behavior (Tellis 2004). First, advertising informs consumers of a product attributes, thereby increasing their awareness and knowledge of the product quality. This is referred to as the informative effect of advertising (Bucklin 1965). Second, advertising may directly influence consumers' product evaluations based on execution cues (e.g., music / copy) and source likability without providing any explicit product information, which is categorized as the persuasive effect of advertising (Batra and Ray 1986). Third, advertising can reinforce consumers' prior product knowledge and experience as well as improve consumer satisfaction, and hence develop repeat buying habits. This is defined as the reinforcement role of advertising (Ehrenberg 1974). In this research, we propose a theoretical framework to illustrate how social and traditional media may affect the market outcomes of new and established products by evoking the different roles played by advertising in consumers' purchase decision making processes. In this framework, we consider the role of advertising as a communication process consisting of three stages: firm's advertising inputs, consumer's mental processes, and market outcomes. A firm's advertising inputs in social and traditional media trigger certain mental processes among consumers such as awareness, persuasion and reinforcement, which result in various market outcomes including new product sales and customer acquisition/retention for established products. Based on the existing theories from advertising, communication and consumer psychology literatures, we identify the dominant role of these two types of media in the consumers' purchase processes, which leads to distinct market outcomes for new and established products respectively. This forms the basis of our argument of how, when, and why advertising in social and traditional media works in the distinct product contexts. The conceptual model of effect of social and traditional media for new and established products is shown in Figure 4. The advertising and communication literatures suggest that certain media characteristics should play a greater role in early stages of product (i.e. new product), while others have more influence later in the lifecycle (i.e. established product). Based on this, we propose that for new product adoption, social media is more effective than traditional media since the recommendations from peer consumers are more persuasive than advertiser's message for new products (i.e. the effect of source credibility on persuasion, see Pornpitakpan 2004). With regards to customer acquisition for established products, social media is again more effective than traditional media since it provides other consumers' product choices online, which reduces the time and effort required to make purchase decisions for new customers, as they can learn from predecessors (informational cascade, Bikhchandani, Hirshleifer, and Welch 1992; 1998). However, with respect to customer retention for established products, traditional media are more effective than social media in reinforcing existing consumers' satisfaction about the product they have already purchased as a result of greater level of reach and positioning power. Below we explain why certain characteristics of these two types of media play a dominant role in certain stages of consumers' mental processes as the product evolves. We argue that the persuasiveness of high-credibility sources and low-credibility sources converge as time passes, and as a result, the high-credibility sources have a substantial decrease in persuasion for established products (Hovland and Weiss 1951; Schulman and Worrall 1970). In the new product context, the informational cascade is underdeveloped, as customers have high perceived risks about the new product, which might increase susceptibility to imitation behavior (Huang and Chen 2006). In addition, source credibility tends to have little effect on persuasion for those consumers who have direct experience with the product (Pornpitakpan 2004). What's more, consumers will have more private information about the product after trial, thus reducing the impact of informational cascade. Next, we will briefly explain the related theories to develop the hypotheses.

The Impact of Social Media on New Product Sales

Research shows that perceived risk is a major determinant of the resistance to innovation adoption (Sheth 1981; Ram and Sheth 1989). Consumers need the aid of personal experience or unbiased sources of information to reduce uncertainty in order to make an adoption decision. Personal experience is costly. Interpersonal communication among consumers enables them to understand the link between the attributes and the benefits of new products in a cost effective way (Hoeffler 2003). In addition, habit toward an existing practice or behavior is another powerful determinant in resistance to new product adoption. An individual is not likely to voluntarily pay attention to new product communication or even try it due to a human tendency to keep the status quo (Sheth 1981). Sometimes, consumers are even unable to see the need for new products (Gourville 2006). In such situations, opinions from friends and acquaintances are often the most influential sources in changing one's attitude or behavior.

Of late, ease of accessibility has lead social media to become a favorite source for consumer advice (Cheung et al. 2009). Moreover, social media enables consumers of various backgrounds to develop relationships, exchange information and build trust among themselves (Dellarocas 2003). Thus, consumers consider social media as a trusted and independent source of information. In the consumer psychology literature, source credibility, the perceived ability and motivation of a message source to provide truthful information, has been identified to have a significant effect on persuasion (Kelman and Hovland 1953; Pornpitakpan 2004). Typically advertisers are considered as partisan, low-credibility sources (Hoch and Ha 1986) because the interest of advertisers generally conflicts with the interests of consumers (Hoch and Deighton

1989). In contrast, the source of information from peer consumers' experiences is considered as more credible as the interests of the source and the consumer are aligned (Susan et al. 2006). Thus, consumer reviews in social media may be perceived to have greater credibility than marketer-generated messages in traditional media (Bickart and Schindler 2001). Source credibility is clearly more likely to affect persuasion when consumers do not have prior product experiences (Rieh and Danielson 2006). This makes the information transmitted by consumers in social media more persuasive and effective than what is communicated by a marketer in cases of new product adoption. Therefore, we propose that:

Hypothesis 1: Social media has a stronger positive impact on new product sales than traditional media.

The Impact of Social Media on Customer Acquisition for Established Products

The aim of customer acquisition is to acquire a customer who otherwise might have purchased a competing brand or might not have purchased the product at all (Libai et al. 2009). Unlike new products where consumers are uncertain about the product quality and benefits, established products have relatively greater information available on product quality and have been adopted by a number of consumers. In the context of established products, rather than worrying about the product quality itself, new customers often find they lack enough knowledge and time to make the optimal purchase decisions from dozens or even hundreds of competing products. This is especially true when very few products available to consumers in the market place are truly differentiated from and superior to the products from competitors (Weilbacher 1993). Under these circumstances, consumers may depend on peer consumers' opinions to make purchase decisions.

Past research has also shown that, surrounded by noisy information from multiple competing products, a new consumer may rationally ignore her own information and choose to follow the crowd (Duan, Gu, and Whinston 2009) since she may believe that other consumers have better information on products than she does (Bonabeau 2004).Thus, buying what others buy could indeed be the most efficient and rational way, as suggested by the Informational Cascades theory (see Bikhchandani, Hirshleifer, and Welch 1992; 1998). This would be especially applicable in the presence of social media, since individuals can easily observe other consumers' adoption decisions such as product popularity and user ratings, in a timely fashion. Thus, as predicted by the Informational Cascades theory, such information provided by peer consumers in social media represents recent adopters' choices and to a great extent influences the followers' purchase decisions, especially for a new customer who has limited information about product value and usability. Therefore,

Hypothesis 2a: Social media has a stronger positive impact on customer acquisition for established products than traditional media.

The Impact of Social Media on Customer Retention for Established Products

For mature products, repeat purchase is the main determinant of sales volume and thus advertising plays a reinforcement role rather than an informative or persuasive role (Ehrenberg 1974). In other words, the role of advertising for established products is to reinforce consumers' feelings of satisfaction about the product that is already being used extensively and enable the purchasing habit to continue to operate in the face of competition. This is because for well-established products, most consumers will have had prior product experience so that their product knowledge structures are likely to be well formed and their product evaluations could be memory based (D'Souza and Rao 1995). In this situation, the consumer does not need to be persuaded, but needs her behavior to be reinforced.

Katz and Lazarsfeld (1955) conclude that mass media are more apt to reinforce current customers rather than convert new customers. Although a very successful YouTube video or a Facebook page might be viewed by a few million consumers, an "average" commercial can generate reach to ten times this number (Communicus 2010). Furthermore, since firms have more control over the message with traditional advertising, traditional media are more successful than social media, which is comprised of consumer driven interactions, in communicating brand attributes and benefits (Communicus 2010). In other words, traditional advertising is more effective at brand positioning and repositioning, thus reinforcing existing consumers' satisfaction about the brand in a better way than social media, which further leads to repurchase. Therefore,

Hypothesis 2b: Traditional media has a stronger positive impact on customer retention for established products than social media.

The Impact of Social and Traditional Media Synergy for New and Established Products

Recognizing that consumers are influenced by a variety of media including TV, radio, print, and Internet, companies are employing "the surround-sound strategy" to reach consumers (Kaplan

2003). The underlying theoretical reasons for cross-media effect have been identified by Stammerjohann et al. (2005). Specifically, when a consumer receives the same message from several different media sources, she will encode the message into her memory in a stronger and clearer way, thus producing positive attitudes toward the advertising messages from different media (Sawyer 1981; Schumann et al. 1990). Social psychologists also propose that greater the number of sources that advocate a position, the more credible the message is perceived to be (Petty and Cacioppo 1986; 1996b). Higher attention and higher perceived message credibility, in turn, determines the number of positive thoughts about the brand and further leads to purchase behavior (MacInnis and Jaworski 1989; Petty and Cacioppo 1986).

As new products often carry some degree of subjective risk to the individual, the credibility of product information is positively related to adoption of new products (Rogers and Shoemaker 1971). Thus, different types of media complement each other in the route to persuasion (Naik and Raman 2003; Dijkstra et al. 2005) in new product adoption. Therefore,

Hypothesis 3a: The interaction between social media and traditional media is positively associated with new product sales.

For a new customer, social and traditional media often complement each other in informing a customer about an established brand which she has not tried yet, thereby leading to customer acquisition. Similar to the argument made above for new products, we propose that, for established products:

Hypothesis 3b: The interaction between social media and traditional media is positively associated with customer acquisition for established products.

Finally, for an existing consumer, companies may use social media to maintain a close relationship with their customers by improving interaction, which complements traditional media in reinforcing consumers' satisfaction about the company and the brand, leading to repurchase. We therefore believe that positive synergies shall exist in this case as well and propose:

Hypothesis 3c: The interaction between social media and traditional media is positively associated with customer retention for established products.

Data and Methodology

Data and Variables

We chose U.S. automobile industry as the setting for the empirical validation of our hypotheses, for several reasons. First, information and data about social media and traditional advertising for new cars is readily available. Second, consumer switching behavior can be observed in the automobile industry with relative ease, as most customers trade in their used cars when purchasing a new vehicle. Moreover, an automobile purchase requires a high level of customer involvement, thereby making the dynamics of customer acquisition and retention become managerially more meaningful (Yoo and Hanssens 2005).

We focused on six brand model cars which were first entered into the market in 2006 (i.e., model year is 2007), viz., Acura RDX, Dodge Caliber, Dodge Nitro, Mazda CX7, Nissan Versa and Toyota Yaris. These specific models were chosen since each model represented a completely new entry into that category by an automaker. For instance, the Acura RDX was the first compact crossover SUV introduced by Acura. By investigating brand-models from their year of introduction, we can analyze the impact of social and traditional media on new product sales in the launch year, and customer acquisition and retention in subsequent years.

We assembled the data from several sources. We collected sales data on these 6 models for the first year in the market from *Automotive News*, which provides U.S. car sales data by make per month. We also purchased monthly customer acquisition and retention data for these models between 2007 and 2009 from R. L. Polk & Co. As for traditional media data, we purchased monthly advertising expenditures on different types of traditional media for each model car from *Kantar Media Intelligence*. The expenditures include a variety of media types including TV, radio, magazines, and newspapers. The sparseness of advertising expenditure within each type of traditional media in the original dataset led us to aggregate these variables into two main types of traditional media -- broadcast and print media -- according to their media characteristics. In addition, we collected social media volume data, which covers online consumer reviews from several main car review cites and blog posts. We treat these two types of social media separately because there are sufficient data on each type and they may operate differently from the conceptual perspective. Specifically, consumer reviews were obtained from *Kelley Blue Book (KBB), Edmunds* and *Consumer Reports*. Blog data were obtained from *Google Blog Search*. Other data including control variables such as model quality and parent brand were collected from *J.D. Power and Associates*. We also collected vehicle type for each model car from *Edmunds*. Moreover, we included the seasonal dummy (e.g., last month of each quarter) to control for unusually-high-demand period.

Model Specification and Estimation

We use a 2-step modeling procedure. First, we adapt the hierarchical interactive model from Naik and Peters (2009) to quantify the magnitudes of the different types of synergies (Figure 5). This model, displayed below, incorporates within-media synergies of traditional and social media and cross-media synergy between them. Specifically, the lower level model combines individual media (e.g., broadcast and print media) into a broader class (e.g., traditional media). Then the resulting factor T (or S), which in turn affects the outcome variable (e.g., new product sales, customer acquisition/retention for established products) either directly and/or interactively along with other media factors. For the sake of parsimony, we only show two types of traditional and social media each in their respective synergy equations, but the model can be generalized to *n* different media. We use Principle Component Analysis (PCA) method to obtain traditional media factor T and social media factor S for both new and established products, which are subsequently used as explanatory variables in the second stage of analysis.

Step 1(PCA) for new and established products:

$$T_t = \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{1t} * X_{2t} \qquad (2.1)$$

$$S_t = \gamma_1 M_{1t} + \gamma_2 M_{2t} + \gamma_3 M_{1t} * M_{2t} \qquad (2.2)$$

where

T_t= traditional media factor that combines the total effect -- direct and interactive -- of all types of traditional media

S_t = social media factor that combines the total effect -- direct and interactive -- of all types of social media

X_{it}= the ith traditional media expenditure

M_{it}= the ith social media volume

β_i: main effect of ith traditional media

β_3: within-media synergy of traditional media

γ_i: main effect of ith social media

γ_3: within-media synergy of social media

Next, following the method used in Osinga, Leeflang and Wieringa (2010), we specify Equations (2.3) and (2.4) for new products. Equation (2.3) captures the effect of traditional media on new product sales via α_1 and the effect of social media on new product sales via α_2. In addition, Equation (2.3) also captures the cross-media interaction between social and traditional media via α_3 for new products. Because we analyze monthly data, we do not include current marketing effects in the sales model, and thus, endogeneity is less of a concern. However, we specify Equation (2.4) to capture the potential relationship between social media volume and traditional media and installed product base. As the correlation between the associated error terms in Equations (2.3) and (2.4) accommodates shocks that may affect the whole system, the seemingly unrelated regression (SUR) is an appropriate estimation approach for this system. In the same vein, Equations (2.5)--(2.8) are developed for established products (acquisition and retention) and estimated simultaneously due to inter-equation correlations. To capture the evolution of the impact of social and traditional media, we estimate the acquisition and retention models separately for each year after the year of launch (i.e. years 2007, 2008 and 2009). A comparison of the coefficients across years and models can then be used to test our hypotheses.

Step 2

(i) for new products:

$$Y_t = \alpha_0 + \alpha_1[T_{t-1}] + \alpha_2[S_{t-1}] + \alpha_3[T_{t-1}]\,[S_{t-1}] + \varepsilon_t \qquad (2.3)$$

$$S_t = \Phi_0 + \Phi_1 T_t + \Phi_2 Y_{t-1} + \eta_t \qquad (2.4)$$

(ii) for established products:

$$A_t = \mu_0^1 + \mu_1^1[T_{t-1}] + \mu_2^1[S_{t-1}] + \mu_3^1[T_{t-1}]\,[S_{t-1}] + \xi_t^1 \qquad (2.5)$$

$$S_t^1 = \lambda_0^1 + \lambda_1^1 T_t + \lambda_2^1 A_{t-1} + \tau_t^1 \qquad (2.6)$$

$$R_t = \mu_0^2 + \mu_1^2[T_{t-1}] + \mu_2^2[S_{t-1}] + \mu_3^2[T_{t-1}]\,[S_{t-1}] + \xi_t^2 \qquad (2.7)$$

$$S_t^2 = \lambda_0^2 + \lambda_1^2 T_t + \lambda_2^2 R_{t-1} + \tau_t^2 \qquad (2.8)$$

[Note: Y_t, A_t, R_t,X_{it} and M_{it} all take log (.) forms]

where

Y_t= new product sales

A_t = customer acquisition (i.e., number of new customers) for established products

R_t = customer retention (i.e., number of returned customers) for established products

ε_t, η_t, $\xi_t^{\ 1}$, $\xi_t^{\ 2}$, τ_t^1, τ_t^2 = unobservables

α_0, Φ_0, μ_0^1, μ_0^2, λ_0^1, λ_0^2: intercept

α_1: effect of last period's traditional media on new product sales

α_2: effect of last period's social media on new product sales

α_3:cross-media interaction effect between last period's traditional and social media on new product sales

Φ_1: effect of current period's traditional media on social media

Φ_2: effect of lagged new product sales on social media

μ_1^1 (μ_1^2): effect of last period's traditional media on customer acquisition (retention) for established products

μ_2^1(μ_2^2): effect of last period's social media on customer acquisition (retention) for established products

μ_3^1(μ_3^2): cross-media interaction effect between last period's traditional and social media on customer acquisition (retention) for established products

λ_1^1(λ_1^2): effect of current period's traditional media on social media

λ_2^1 (λ_2^2): effect of lagged customer acquisition (retention) on social media

We apply the residual centering procedure (e.g., Jong, Ruyter, and Wetzels 2005) to handle multicollinearity. Specifically, each interaction term was first regressed on its two main components and the residuals obtained were used as explanatory variables.

Results and Discussion

Overall Descriptive Findings

Table 7 and 8 present the summary statistics and correlations between key variables in this study. The mean monthly new product sales in the log form is 8.01, and the average monthly number of new (returning) customers in the log form is 7.93 (5.03). The traditional and social media factors for new and established products are extracted from their respective original sub-datasets.

The Impact of Social Media and Traditional Media on New Product Sales: Results

The results of the principle component analysis and the resulting traditional and social media factors are shown in Table 9, while Table 10 shows the results from equations (2.3) and (2.4). Both traditional and social media have a significant impact on new product sales, but social media has a larger impact than traditional media (0.119, $p<0.001$; 0.027, $p<0.1$), which supports our hypothesis H1. This indicates that consumer-generated media is more effective in generating sales for new products than marketer-generated media, probably due to a greater level of source credibility. Interestingly, we find that the coefficient for the interaction effect between social and traditional media on new product sales is negative and significant (-0.004, $p<0.05$), which implies that social and traditional media are substitutable for new products. This result contradicts to our hypothesis H3a. The possible reason is that there is limited product information in the market. Consumers could get product information from traditional advertising or social media according to their media preferences and habits. As we know, those consumers who buy new products are mostly innovators. Probably, the more product information they get from traditional media, the less information they need from social media, and vice versa.

In addition, our results indicate that the quality of the new car model has no significant impact on sales. However, surprisingly the quality of the parent brand is found to be significant and negatively related to sales (0.018, $p<0.001$). This seemingly contradictory findings may indicate that in our dataset, the quality of the specific new car model could not be inferred from its parent brand when consumers make purchase decisions. With regard to the social media equation, our findings indicate that only lagged sales is significant and positively related to social media (0.899, $p<0.001$), which implies that the more new cars are sold, the more people would like to talk about. However, the coefficients for variables such as traditional media expenditure, the parent brand and model quality, and body style are found to be insignificant to social media.

The Overall Impact of Social and Traditional Media on Customer Acquisition and Retention for Established Products

The results of SUR estimation (see Table 10) show that the coefficients for both social and traditional media are significant and social media has a greater impact on customer acquisition for established products than traditional media (0.057, $p<0.05$; 0.049, $p<0.001$), which is consistent with our hypothesis H2a. However, the interaction effect between social and traditional media on customer acquisition for established products is not significant, which implies that the complementary and substitutable effect of both types of media may be offset to acquire new customers in the established product context. In contrast, we find that traditional media has a larger effect on customer retention for established products than social media and the coefficients for both variables are significant (0.052, $p<0.001$; 0.049, $p<0.05$), which supports hypothesis H2b. Moreover, consistent with our hypothesis H3c, the coefficient for the interaction between social and traditional media on customer retention for established products is significant and positive (0.005, $p<0.05$). This result implies that both social and traditional media are complementary in attracting returned customers for established products.

Our results from the social media equations in the customer acquisition model indicate that traditional media has a negative impact on social media volume (-0.121, $p<0.001$). Existing psychology literature suggests that interesting products drive more WOM (Berger and Schwartz 2011). The potential explanation for this finding is that when individuals receive much product information from the source of traditional media, they become familiar with the product, and thus they may feel not interesting to talk about it. Also, the coefficient for lagged customer acquisition is significant and positive (0.592, $p<0.001$), indicating that installed base positively affects social media volume. However, other variables such as model quality, parent brand and body style do not affect social media. Similarly, as for the social media equation in the customer retention model, traditional media factor has a significant and negative impact and lagged customer retention has a significant and positive impact on customer retention respectively (-0.118, $p<0.001$; 0.488, $p<0.001$). Unlike the customer acquisition model, the effect of model quality on social media factor is significant and negative in the customer retention model (-0.621, $p<0.1$). This is probably because low quality products are more likely to be discussed by returned customers, who are familiar with the product very well. Other variables such as parent brand and body style are found to have no significant effect on social media factor in the customer retention model.

The Dynamic Impact of Social Media and Traditional Media on Customer Acquisition and Retention for Established Products: Yearly Results

Table 11 presents the principal components of traditional and social media for established products in year 2007, 2008 and 2009 respectively. The result from the SUR estimation for customer acquisition equation in each year shows that social media has a larger impact on customer acquisition for established products than traditional media, consistent with Hypothesis H2a (Table 12). A further analysis suggests that the impact of social media on customer acquisition first increases and then decreases, whereas the impact of traditional media declines followed by a big jump over time. The potential explanation for this interesting result could be the trend of WOM effects may be corresponding to consumer's learning curve and the carryover effect of traditional advertising may take effect as time passes. Moreover, we find the cross-media synergy between social and traditional media is significant and positively associated with customer acquisition only for the established products in 2008 (0.009, $p<0.1$). With regard to control variables, the results show that model quality is negatively associated with customer acquisition in 2007 and 2009. Parent brand and body style are both negatively associated with customer acquisition in each year. However, we do not find any impact of seasonality on customer acquisition in every year to be statistically significant.

As for social media equation in the customer acquisition model, we find that traditional media is negatively related to social media factor in 2007 and 2008, but it is positively related to social media factor in 2009. The possible reason is that individuals tend to be curious and talk about the cars when they could not get much information from traditional advertising at the early stage. As time goes, more traditional advertising could stimulate consumers interests on the car they've already been familiar with. As expected, lagged customer acquisition all have positive impacts on social media factor for these 3 individual years. In addition, model quality is negatively and then positively associated with social media factor as well as becomes insignificant eventually. And parent brand is positively related to social media factor in 2007 and 2009, but it is negatively related to that in 2008. We also find body style initially has a positive impact on customer acquisition in 2007 and 2008, and then it has a negative impact in 2009. The signs of these variables change in different years, probably due to consumers' learning process and preferences on the topic of product conversation evolve over time.

Furthermore, the results of SUR estimation from the customer retention model suggest that traditional media has less impact on customer retention than social media in 2007 and 2008, but it has a much larger impact on customer retention in 2009 (see Table 12). In particular, the effect of traditional media first decreases and then increases, in contrast, the effect of social media grows and then declines over time. However, we find the cross-media synergy to be statistically insignificant in each year. In terms of control variables, the coefficient for model quality is significant and negative only in 2007 and the coefficient for parent brand is significant and negative only in 2009. Moreover, body style is negatively associated with customer retention in 2007 and 2008. And we do not find seasonality has any impact on customer retention. Regarding the social media equation, similar to previous results in the customer acquisition model, traditional media has a negative impact on social media factor in 2007 and 2008, however, it has a positive impact in 2009. Also, the coefficients for lagged customer retention are all positive in each year. Quality and parent brand are found to be negative and statistically significant in 2008, whereas only parent brand is found to be positively associated with customer retention in 2009. As for seasonality, our finding shows it is negatively related to customer retention in 2009.

The above discussion shows that we find mixed support for our hypotheses H2a and H2b when we use yearly data to compare the dynamic effect of social and traditional media on established product performance. This implies that the carryover effect and recency effect of social media may play a large role in turn at distinct stages as products evolve .

Conclusion

Summary

In this study, we develop a conceptual framework and hypotheses to examine and compare the impacts of social and traditional media on new product sales, customer acquisition and retention for established products. In addition, we take a further step to investigate the dynamic effect of social and traditional media on product performance in the established product context. Furthermore, we also test the within-media synergies of social and traditional media as well as the cross-media synergy between social and traditional media in different product contexts. Consistent with our hypotheses, the results indicate that social media has a greater effect on new product sales than traditional media. Our overall findings for established products also suggest that social media is more effective in acquiring new customers than traditional media, in contrast, traditional media is more effective in attracting returned customers than social media. A further analysis on the dynamic impact of social and traditional media in the established product context implies that the effect of social media on customer acquisition and retention first increases and then decreases, whereas the impact of traditional media declines followed by a big jump over time. With regard to the interaction effect between social and traditional media in different product contexts, we surprisingly find both types of media are substitutable for new product sales and complementary for customer retention. However, the cross-media interaction does not have any impact on customer acquisition for established products.

The contributions of this research are as follows. First, this is the first study to compare the impact of social and traditional media on product performance (i.e., sales/customer acquisition and retention) for new and established products respectively. Second, this study integrates and investigates the different types of synergies in the current multi-media world such as the within-media synergies of traditional and social media as well as the cross-media synergy between these two types of media. Third, this study also demonstrate that the cross-media synergy between social and traditional media could be different for different product contexts in this new media landscape, which challenges the traditional view on media synergy.

Managerial Implications

Our findings that social media is more effective than traditional media in generating new product sales and acquiring new customers for established products while traditional media is more effective in customer retention for established products than social media imply that managers should choose right media strategy with different marketing goals under different product contexts. Although social media is substantially used and emphasized by many companies recently, traditional media still plays an important role under some circumstances. Moreover, our findings also indicate that the cross-media synergies between social and traditional media could be different in different product contexts. This result helps managers to understand that in the new media landscape, the traditional view of media synergy should be updated and the synergy effect between these two types of media should be strategically utilized for resource allocation.

Limitation and Future Research

This research has some limitations that suggest the future research directions. First, we may incorporate more types of social media (e.g., social networking sites etc.) to extend the current model. As we collected social media data from 2006 in this study, social networking sites such as Facebook.com and twitter were not so popular as it is now, we could not get those data for this current study. Thus, in the future we may cover more types of social media in the model to make the media landscape complete. Second, we only use social media volume to measure the impact of social media on product performance in this study. In the future research, we may also use other social media metrics such as valence and content to examine the effect of social media from other perspectives. Third, the context for this study is automobile industry, which is representative of high-involvement products. We may extend to other high-involvement product contexts to test the conceptual framework and hypotheses in order to generalize the findings of this study.

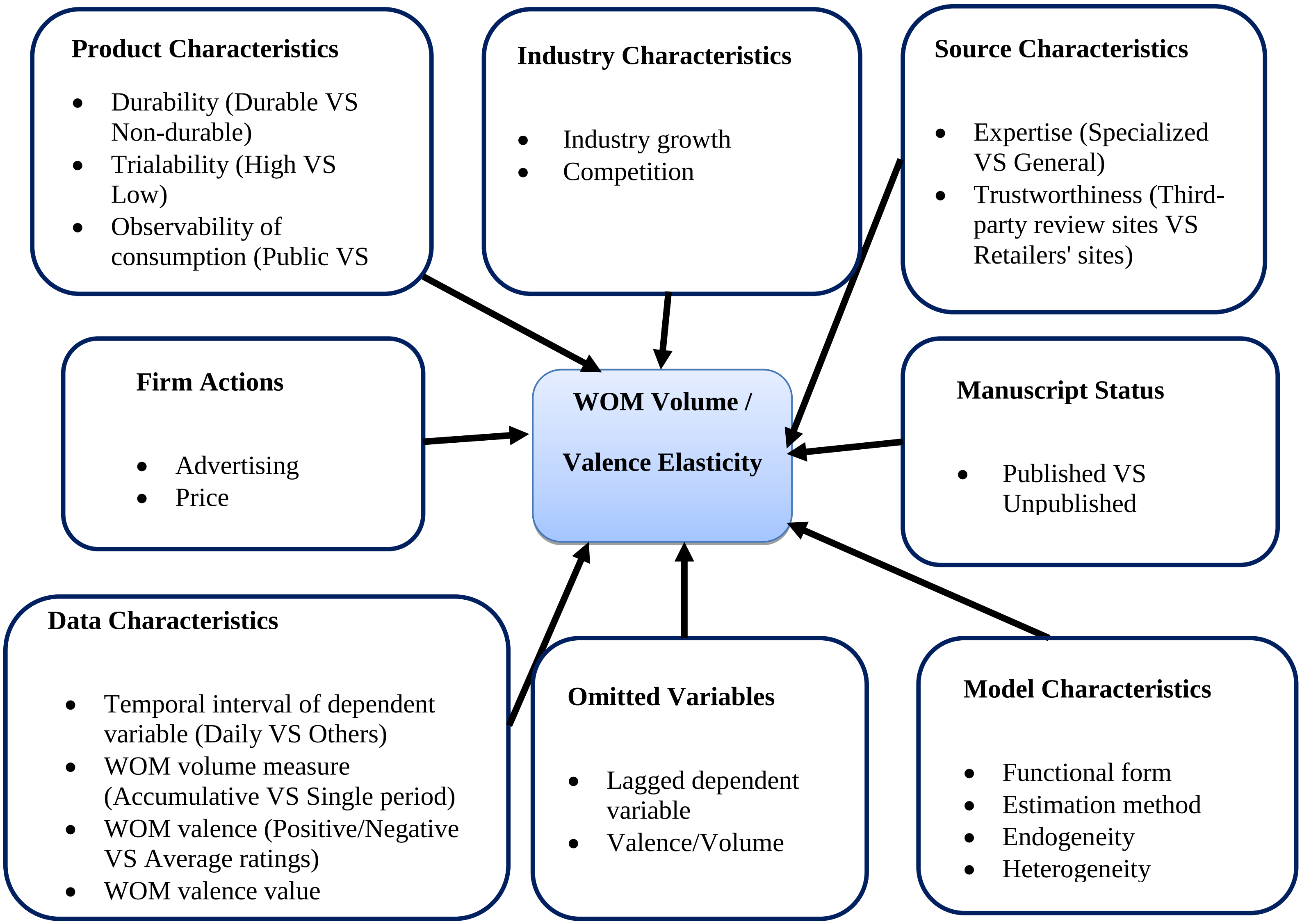


Figure 1 A conceptual framework of the factors influencing WOM effect

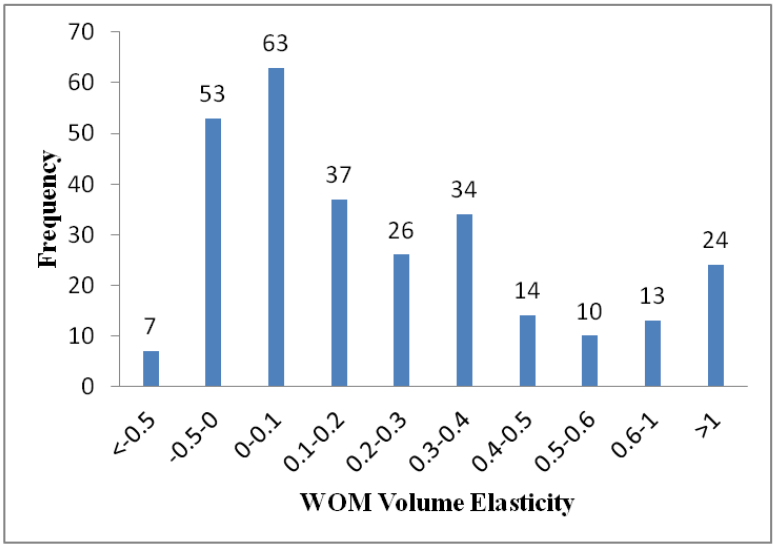


Figure 2 Frequency distribution of WOM volume elasticity

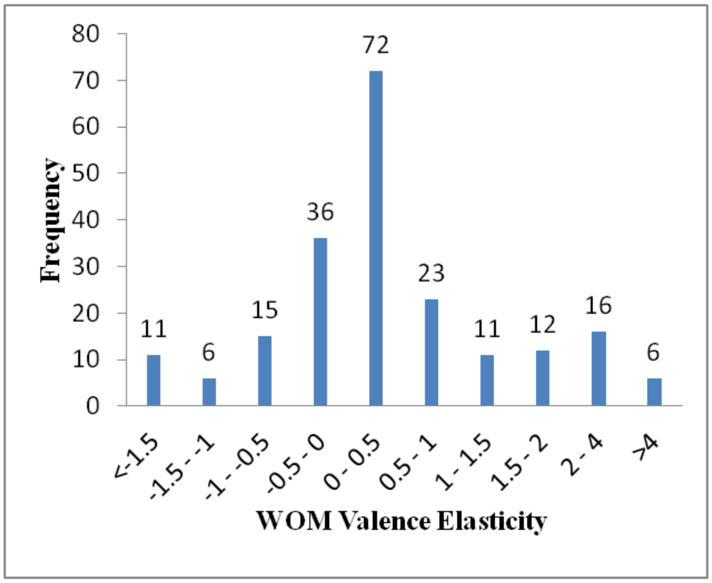
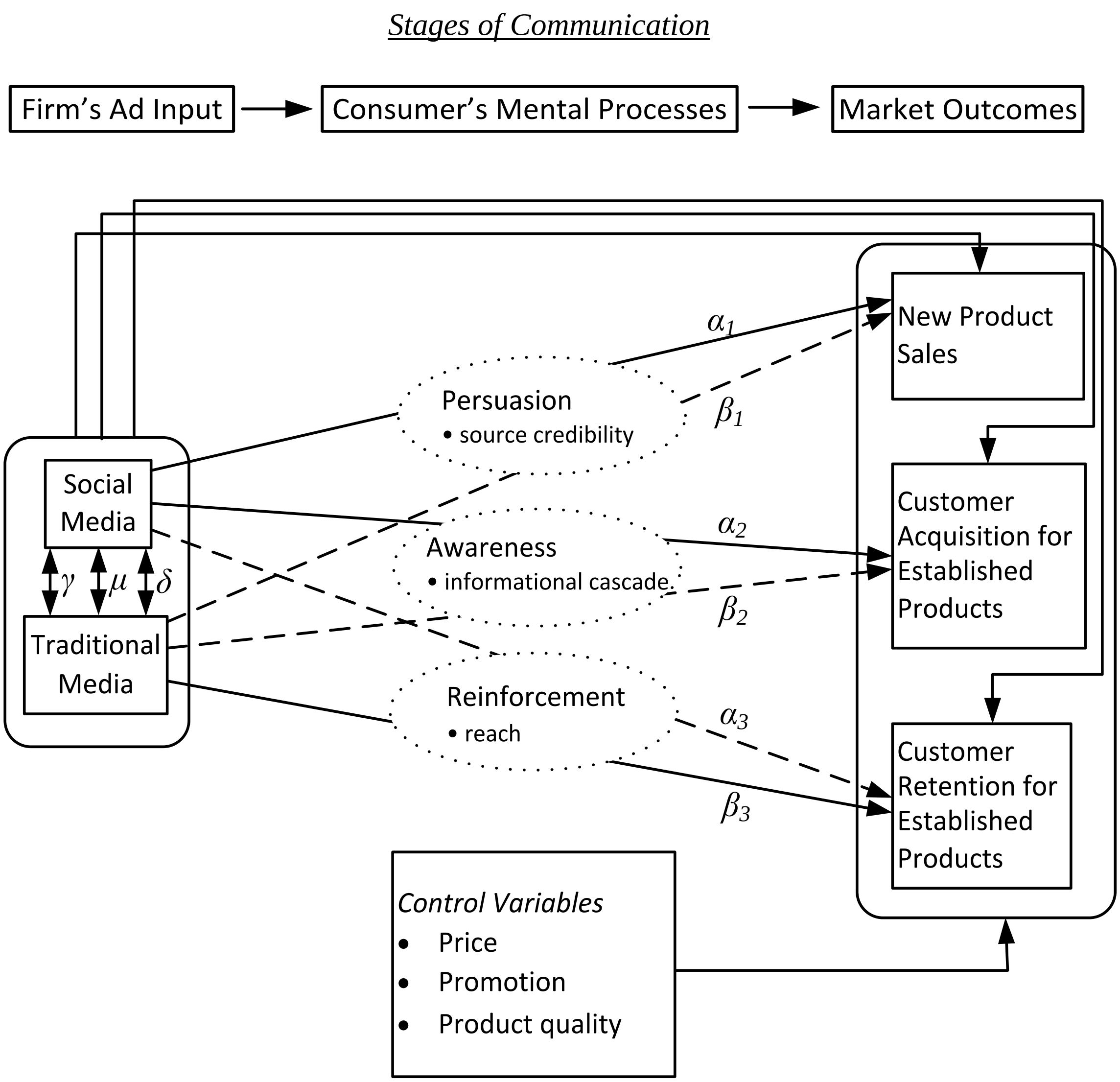


Figure 3 Frequency distribution of WOM valence elasticity



Corresponding Hypotheses:

H_{1a}: $\alpha_1 > \beta_1 > 0$

H_{2a}: $\alpha_2 > \beta_2 > 0$

H_{2b}: $\beta_3 > \alpha_3 > 0$

Figure 4 Model of Ad effectiveness (Adapted from Tellis (2004))

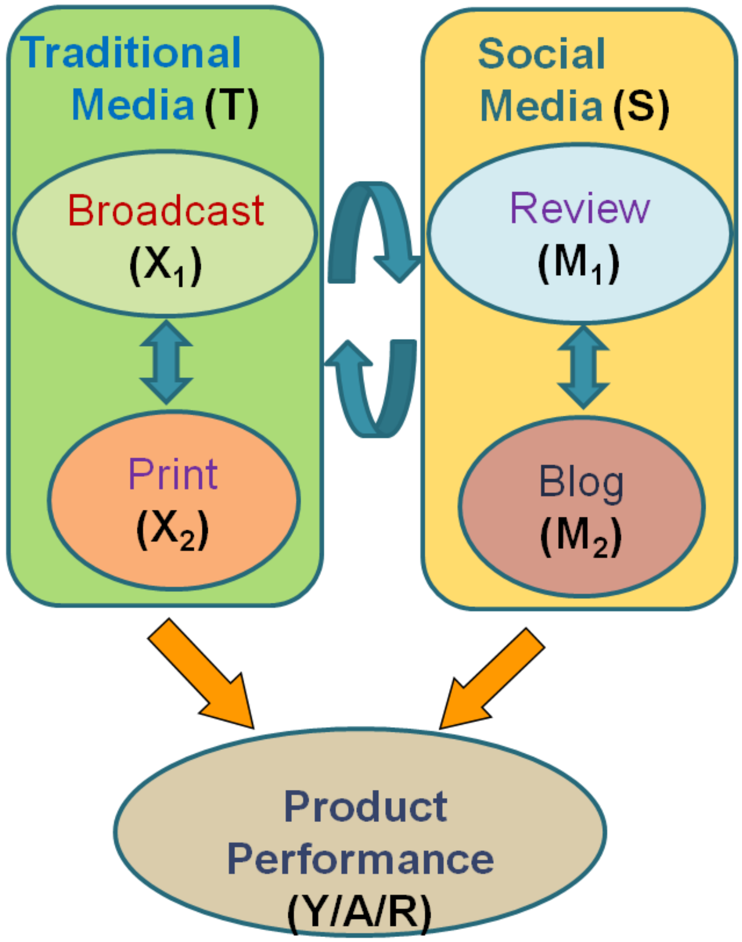


Figure 5 Media hierarchical interactive model

Table 1 Taxonomy of WOM

		WOM Audience Size	
		Small	*Large*
WOM Form	*Private*	(I) traditional WOM referral	(II) text messaging
	Public	(III) social networking sites	(IV) blogs, discussion forum, online product reviews

Table 2 Expected relationships, rational, and interpretation of results

Variable/ Level	Expected Sign (Vol/Val)		Rational	Actual Sign (Vol/Val)		Interpretation
Product Characteristics						
Product durability Durable Non-durable	(+)	(+)	WOM effect is greater for durables than for non-durables. Durable products are characterized by large interpurchase intervals and high-unit-cost than non-durable products, and thus, consumers are more actively seeking information to reduce risk for durable products.	(+)	NA	Results support the expectations.
Product trialability High Low	(-)	(-)	WOM effect is greater for products with low trialability than for those with high trialability. For a product with low trialability, a peer consumer's product experience can serve as a quality signal, which lowers the perceived risk in the purchase decision-making process.	(-)	(-)	Results support the expectations.
Observability of product consumption Public Private	(-)	(-)	WOM effect is greater for private products than for public products. It is harder for consumers to get product information by observation for private than for public products, and thus, they have greater motivation to process WOM information ofproducts consumed in a private setting.	(-)	(-)	Results support the expectations.

Variable/ Level	Expected Sign (Vol/Val)		Rational	Actual Sign (Vol/Val)		Interpretation
Industry Characteristics						
Industry growth	(+)	(+)	WOM effect is greater for industry with higher growth as WOM can help individuals make more accurate predictions of the fit of product with their preferences in a growth industry with frequent product changes.	NS	(-)	As the signal of popularity, volume is perceived as more product-specific in different industries, hence, its effect does not depend on the industry growth. WOM valence may be perceived as less unbiased in the high-growth than slow-growth industry due to self-selection bias, and thus having a discounting effectiveness.
Competition	(+)	(+)	WOM effect is greater for industry with more competitors as when consumers have more product options, the uncertainty about which alternative to choose results in increased product information search.	(-)	(-)	When a number of competitors co-exist in an industry, consumer heterogeneity in preferences may results in diverse endorsement for different brands. WOM effect may be reduced by such crowded information.
Source Characteristics						
Expertise of WOM hosted platform Specialized General	(+)	(+)	WOM from "specialized" review sites is more effective than that from "general" ones. It contains a significant amount of product information which is often more specialized, or considered as having a high level of expertise, and thus, being perceived as more credible to consumers.	(+)	NS	The ratings from those expert consumers may not be perceived as credible as they are expected, probably because those ratings are very subjective to expert users' personal preferences.
Trustworthiness of WOM hosted platform Independent third-party review sites Retailers' sites	(+)	(+)	WOM from independent third-party review sites is more effective than that from retailers' sites. Compared to retailers' sites, independent third-party review sites provide more objective information and are not subject to censoring concerns, thus being perceived as more unbiased and trustful sources.	(+)	(+)	Results support the expectations.

Variable/ Level	Expected Sign (Vol/Val)		Rational	Actual Sign (Vol/Val)		Interpretation
Firm Action						
Advertising Omitted Included	(+/ -)	(+/ -)	Increased advertising can stimulate product awareness and WOM; increased WOM can also trigger product awareness and strengthen the effect of advertising. In addition, more advertising signals a product of high quality, which may induce high ratings. As advertising is likely to be positively related to WOM volume/valence and sales, we expect the omission of advertising to introduce a positive bias in the WOM volume/ valence elasticity.	NS	NS	Both positive and negative correlations between advertising and WOM exist in different studies in our database, so that the complementary and substitutable effect between these two constructs may be offset.
Price Omitted Included	(+)	(+)	Price may stimulate WOM (number of reviews and higher ratings) as consumers may enjoy telling others about the low prices they find or pay and are likely to provide positive reviews about the low price. As price is likely to be correlated negatively with WOM volume/valence and sales, we expect the omission of the price variable to bias the WOM volume/valence elasticity positively.	NS	NS	For the products in our study, prices tend to stay fixed over a long time period.
Distribution Omitted Included	(+)	(+)	A greater level of product distribution tends to generate herding behavior among consumers, which leads to increased WOM. In addition, products that are anticipated to receive positive reviews are also widely distributed. As distribution is likely to be positively correlated to WOM volume/valence and sales, we expect the omission of distribution to bias the WOM volume/valence elasticity positively.	NS	(+)	For certain products in our study, a lower level of distribution also stimulate consumers' curiosity and WOM, which balances out the positive correlation between these two variables.

Variable/ Level	Expected Sign (Vol/Val)		Rational	Actual Sign (Vol/Val)		Interpretation
Data Characteristics						
Temporal interval of dependent variable Daily Others	(+)	(+)	We expect a lower level of temporal aggregation (e.g., daily instead of weekly or monthly) of the dependent variable would positively bias the WOM volume and valence elasticities, because when the dependent variables (e.g., sales) are aggregated to a longer time period, finer fluctuations may be lost.	(+)	NS	Valence may have a recency effect on sales effect.
WOM volume measure Accumulative Single period	(-)	(-)	Individuals tend to weigh recent information more heavily than earlier information. In fact, consumers may not read all reviews due to the opportunity cost of time. Also, online WOM tends to fade away more quickly than face-to-face WOM due to lower trust and fewer social interactions in the virtual world. Thus, we expect the sales response to accumulative WOM is less than that to single period (e.g., current/previous time period) WOM.	NS	NS	WOM also generates strong carryover effect (e.g., Liu 2006; Trusov, Bucklin, and Pauwels 2009), which may negate the recency effect on consumer decision-making.
WOM valence measure Positive ratings Negative ratings Average ratings		(+) (-)	We expect the WOM valence measure of extremely positive ratings (e.g., 5 star in a 1-5 star rating scale)/extremely negative ratings (e.g., 1 star in a 1-5 star rating scale) would positively/negatively bias the valence elasticity as a more polarized set of reviews may be perceived as more informative by consumers than moderate ones (average ratings).		NS (-)	As many of the extant studies concentrate on non-durable products, personal tastes play a large role in these product categories. Thus, the favorable ratings for these products may be viewed as relatively ambiguous, which could prompt more uncertainty in the evaluation.
WOM valence value		(-)	We expect higher valence ratings to bias the WOM valence elasticity negatively. The lower the valence ratings, the poorer the product quality are perceived, and thus, the stronger effect they have on consumer's decisions according to prospect theory.		NS	The variation in the valence of reviews in our studies is so limited that it does not impact on elasticity estimates.

Variable/ Level	Expected Sign (Vol/Val)		Rational	Actual Sign (Vol/Val)		Interpretation
Omitted Variables						
Lagged dependent variable Omitted Included	(+)	(?)	We expect the omission of lagged sales to positively bias WOM volume elasticity as lagged sales are likely to be correlated positively with current-period WOM volume and sales. No prior expectations for the effect on valence elasticities.	(+)	NS	Valence ratings could be either positively or negatively correlated with lagged sales.
Valence/Volume Omitted Included	(-)	(-)	Valence of ratings tends to trend downward as more reviews are accumulated due to self-selection bias. We expect the omission of valence (volume) to bias the WOM volume (valence) elasticity estimate negatively as valence is likely to be negatively related to volume and positively related to product sales.	(-)	NS	For some product categories, valence may not be positively associated with sales.
Model Characteristics						
Functional form Multiplicative Others	?	?	No prior expectations.	NS	NS	There is no single "best" model for WOM modeling.
Estimation method OLS Others	?	?	No prior expectations.	NS	(+)	No satisfactory explanation.
Endogeneity Omitted Included	(-)	(-)	We do not have theoretical reasoning, but consistent with previous studies (e.g., Bijmolt, van Heerde, and Pieters 2005; Sethuraman, Tellis, and Briesch 2011), we expect the failure to account for endogeneity to bias the WOM volume and valence elasticities negatively.	NS	(-)	
Heterogeneity Omitted Included	?	?	No prior expectations.	NS	NS	

Variable/ Level	Expected Sign (Vol/Val)		Rational	Actual Sign (Vol/Val)		Interpretation
Other factors						
Manuscript status Published Unpublished	(+)	(+)	We expect that WOM volume and valence elasticities in published papers to be higher than those in unpublished papers.	NS	NS	No publication bias.
Interaction effects						
WOM valence measure * Product trialability	(+)	(+)	For high trailability products, extremely positive or negative ratings may have greater influence on WOM valence elasticities than average ratings because consumers may selectively pay attention to the reviews that totally confirm or disconfirm to their own opinions when WOM serves as a complementary source to make purchase decisions for products easier to try. In contrast, for low trailability products, average ratings may be more effective than extremely positive or negative ones since average ratings can be perceived as the "true" quality of a product, which are used to compare and choose among a few alternatives.	NS	(+)	For high trailability products, consumers may be indifferent with extreme and average ratings.
WOM valence measure * Observability of product consumption	(-)	(-)	For publicly consumed products, extremely positive or negative ratings may have fewer influence on WOM valence elasticities than average ratings because when individuals buy those products, they tend to conform to social norm, that is, opinions from the majority of the group (shown by average ratings). However, extreme ratings would be more effective than average ratings for products consumed in a private setting since the productexperience is more subjective, which leads extremely positive or negative ratings to be perceived as credible in making purchase decision.	NS	NS	For products consumed in a public/private setting, consumers may be indifferent with extreme and average ratings.

Variable/ Level	Expected Sign		Rational	Actual Sign		Interpretation
Interaction effects						
WOM valence measure * Industry growth	(+)	(+)	For industry with a higher level of growth, extremely positive or negative ratings may have greater influence on WOM valence elasticities than average ratings because in an environment of frequent product changes, extreme ratings may perceived as more informative for consumer learning than average ratings.	(+)	(+)	Results support the expectations.
WOM valence measure * Competition	(+)	(+)	For industry with increasing competition, extremely positive or negative ratings may have greater influence on WOM valence elasticities than average ratings because when consumers face several competing products, which are difficult to differentiate from each other, extreme ratings would like to be more diagnostic and helpful for consumers to make purchase decisions than average ratings.	(+)	(+)	Results support the expectations.

Table 3 Factors of the meta-analysis

Category Variable	Coding Scheme
Product Characteristics	
Product durability	Base: Non-durable Durable: 1 (vs 0 for not)
Product trialability	Base: Low High: 1 (vs 0 for not)
Observability of product consumption	Base: Private Public: 1 (vs 0 for not)
Industry Characteristics	
Industry growth	Continuous
Competition	Continuous
Source Characteristics	
Expertise of WOM hosted platform	Base: General Specialized: 1 (vs 0 for not)
Trustworthiness of WOM hosted platform	Base: Retailers' sites Independent third-party review sites: 1 (vs 0 for not)
Firm Action	
Advertising	Omitted: 1 (vs 0 for not)
Price	Omitted: 1 (vs 0 for not)
Distribution	Omitted: 1 (vs 0 for not)
Data Characteristics	
Temporal interval of dependent variable	Base: Others Daily: 1 (vs 0 for not)
WOM volume measure	Base: Single (e.g., current or previous) period Accumulative:1 (vs 0 for not)
WOM valence measure	Base: Average ratings Positive ratings: 1 (vs 0 for not) Negative ratings: 1 (vs 0 for not)
WOM valence value	Continuous
Omitted Variables	
Lagged dependent variable	Omitted: 1 (vs 0 for not)
Valence	Omitted: 1 (vs 0 for not)
Volume	Omitted: 1 (vs 0 for not)
Model Characteristics	
Functional form	Base: Others Multiplicative: 1 (vs 0 for not)
Estimation method	Base: others OLS: 1 (vs 0 for not)
Endogeneity	Not accounted for: 1 (vs 0 for accounted for)
Heterogeneity	Not accounted for: 1 (vs 0 for accounted for)
Other factors	
Manuscript status	Base: unpublished Published: 1 (vs 0 for not)

Table 4 Summary statistics of key variables

	WOM Volume Model (N=281)				WOM Valence Model (N=208)			
Variable	Mean	S. D.	Min.	Max.	Mean	S. D.	Min.	Max.
Dependent Variable (DV)								
Volume elasticity	0.256	0.505	-1.443	2.98				
Valence elasticity					0.455	1.651	-5.86	7.73
Independent Variable (IV)								
Product durability	0.516	0.501	0	1				
Product trialability	0.736	0.441	0	1	0.687	0.465	0	1
Observability of consumption	0.587	0.493	0	1	0.572	0.496	0	1
Industry growth	-18.13	55.14	-119	140	-4.191	68.88	-119	140
Competition	60.33	126.83	7	687	101.85	166.76	7	687
Expertise of WOM source	0.409	0.493	0	1	0.399	0.491	0	1
Trustworthiness of WOM source	0.719	0.450	0	1	0.462	0.499	0	1
Advertising	0.534	0.499	0	1	0.856	0.352	0	1
Price	0.591	0.493	0	1	0.365	0.483	0	1
Distribution	0.612	0.488	0	1	0.712	0.454	0	1
Temporal interval of DV	0.217	0.413	0	1	0.394	0.489	0	1
WOM volume measure	0.441	0.497	0	1				
WOM valence: positive ratings					0.202	0.402	0	1
WOM valence: negative ratings					0.202	0.402	0	1
WOM valence value					0.665	0.179	0.233	0.96
Omitted variable: lagged DV	0.651	0.477	0	1	0.769	0.422	0	1
Omitted variable: valence	0.316	0.466	0	1				
Omitted variable: volume					0.082	0.275	0	1
Functional form: multiplicative	0.085	0.280	0	1	0.120	0.326	0	1
Estimation method: OLS	0.509	0.501	0	1	0.591	0.493	0	1
Endogeneity	0.324	0.469	0	1	0.375	0.485	0	1
Heterogeneity	0.292	0.455	0	1	0.312	0.465	0	1
Manuscript status	0.740	0.439	0	1	0.851	0.357	0	1

Table 5 Estimation results of HLM

	WOM Volume Elasticity			WOM Valence Elasticity		
Variable	*Estimate*	*S.E.*	*p-Value*	*Estimate*	S.E.	*p-Value*
Constant	-0.328	0.337	0.331	1.758	1.385	0.204
Product Characteristics						
Product durability						
Non-durable						
Durable	0.527	0.188	0.005			
Product trialability						
Low						
High	-0.456	0.136	0.001	-2.640	0.718	<0.001
Observability of consumption						
Private						
Public	-0.444	0.155	0.004	-2.159	0.766	0.005
IndustryCharacteristics						
Industry growth	-0.001	0.001	0.225	-0.009	0.003	0.005
Competition	-0.001	0.0005	0.02	-0.006	0.001	<0.001
SourceCharacteristics						
Expertise of WOM hosted platform						
General						
Specialized	0.274	0.146	0.062	0.376	0.541	0.486
Trustworthiness of WOM hosted platform						
Retailers' sites						
Independent third-party review sites	0.649	0.176	<0.001	2.729	0.632	<0.001

	WOM Volume Elasticity			WOM Valence Elasticity		
Variable	*Estimate*	*S.E.*	*p-Value*	*Estimate*	*S.E.*	*p-Value*
Firm action						
Advertising						
Included						
Omitted	0.053	0.165	0.749	-0.547	0.622	0.379
Price						
Included						
Omitted	0.218	0.187	0.245	0.339	0.558	0.544
Distribution						
Included						
Omitted	-0.112	0.103	0.278	1.476	0.506	0.004
DataCharacteristics						
Temporal interval of DV						
Others						
Daily	0.461	0.143	0.001	0.218	0.457	0.633
WOM volume measure						
Single period						
Accumulative	-0.127	0.108	0.240			
WOM valence measure						
Average ratings						
Positive ratings				-0.145	1.127	0.898
Negative ratings				-4.852	1.127	<0.001
WOM valence value				-1.309	1.201	0.276

	WOM Volume Elasticity			WOM Valence Elasticity		
Variable	*Estimate*	*S.E.*	*p-Value*	*Estimate*	*S.E.*	*p-Value*
Omitted Variables						
Lagged DV						
Included						
Omitted	0.352	0.107	0.001	0.249	0.292	0.394
Valence						
Included						
Omitted	-0.417	0.152	0.006			
Volume						
Included						
Omitted				-0.261	0.547	0.634
ModelCharacteristics						
Function form						
Others						
Multiplicative	-0.061	0.199	0.759	-0.853	0.819	0.298
Estimation method						
Others						
OLS	0.136	0.111	0.218	1.552	0.433	<0.001
Endogeneity						
Accounted for						
Not accounted for	-0.0005	0.102	0.996	-0.844	0.297	0.004
Heterogeneity						
Accounted for						
Not accounted for	0.022	0.133	0.869	0.081	0.393	0.838
Other factors						
Manuscript status						
Unpublished						
Published	0.111	0.169	0.513	0.652	0.487	0.181

	WOM Volume Elasticity			WOM Valence Elasticity		
Variable	*Estimate*	*S.E.*	*p-Value*	*Estimate*	*S.E.*	*p-Value*
Interaction effects						
Product trialability * Positive ratings				0.120	0.911	0.895
Observability of consumption * Positive ratings				-1.027	1.015	0.312
Industry growth * Positive ratings				0.015	0.005	0.001
Competition * Positive ratings				0.015	0.008	0.063
Product trialability * Negative ratings				2.559	0.911	0.005
Observability of consumption * Negative ratings				0.272	1.015	0.789
Industry growth * Negative ratings				0.018	0.005	<0.001
Competition * Negative ratings				0.034	0.008	<0.001

Table 6 Empirical generalizations about advertising elasticity of traditional media

Study	Product Category	Type of Media	Empirical Generalization
Parsons (1975)	A quality household cleanser (new/ established)	General	Advertising elasticity declines over time. i.e. The advertising elasticity was initially 1.0252, declined to 0.2703 by 1886, and ended up at 0.278 in 1915.
Assmus, Farley and Lehmann (1984)	Multiple (meta-analysis)	General	The mean short-term elasticity is 0.22. Elasticities are higher for advertised food products and higher in Europe than in the U.S. Short-term elasticities vary systematically with data interval. Cross-sectional data produce higher short-term elasticities than time series.
Sethuraman and Tellis (1991)	Multiple (meta-analysis)	General	The average advertising elasticity is 0.11. Advertising elasticity declines over time. Advertising elasticity is higher for durable products than frequently purchased nondurable products,and for intermediate/higher levels of temporal aggregation (quarterly and yearly). But it is smaller for lower (less than monthly) levels of temporal aggregation.
Lodish et al. (1995a)	Split cable (new/ established)	TV	The average advertising elasticity is 0.13. The elasticity for new products is 0.26, which is five times higher than that for established products (0.05).
Vakratsas and Ambler (1999)	Multiple (meta-analysis)	General	Short-term advertising elasticities are small and decrease over time. Returns to advertising diminish fast for mature, frequently purchased packaged goods.
Hu, Lodish and Krieger (2007)	Multiple (established)	TV	The average elasticity of two different tests (BehaviorScan& Matched-Market) for established products is 0.113.
Sethuraman, Tellis and Briesch (2010)	Multiple (meta-analysis)	General	The average short-term and long-term advertising elasticity is 0.12 and 0.24 respectively. Advertising elasticity has declined over time. It is higher a) for durable goods than non-durable, b) for yearly data than for quarterly data, and c) when advertising is measured in Gross Rating Points than in monetary term, d) in Europe than in North America. The mean long-term advertising elasticity is 0.24. Advertising elasticity does not decrease during recession.

Table 7 Summary statistics for new products

		M	SD	1	2	3	4	5	6	7	8
1	**ln(Sales)**	8.01	1.59	1							
2	**TraditionalMedia**	13.64	7.48	0.10	1.00						
3	**SocialMedia**	9.80	3.68	0.56	0.17	1.00					
4	**T-S Synergy**	138.47	81.91	0.31	0.85	0.55	1.00				
5	**Quality**	2.41	0.45	0.01	0.23	0.01	0.21	1.00			
6	**ParentBrand[a]**	131.29	16.51	-0.20	0.05	0.03	0.05	-0.71	1.00		
7	**Body Style**	0.50	0.50	-0.62	-0.05	-0.06	-0.10	-0.19	0.62	1.00	
8	**Seasonality**	0.33	0.47	0.05	0.04	0.03	0.08	0.02	0.04	0.03	1.00

Table 8 Summary statistics for established products

		M	SD	1	2	3	4	5	6	7	8	9
1	**ln(Acquisition)**	7.93	0.76	1.00								
2	**ln(Retention)**	5.03	0.64	0.84	1.00							
3	**TraditionalMedia**	6.08	6.36	0.27	0.42	1.00						
4	**SocialMedia**	13.22	2.09	0.18	0.09	-0.33	1.00					
5	**T-S Synergy**[b]	0.18	13.67	0.08	0.11	-0.01	0.02	1.00				
6	**Quality**	2.55	0.47	-0.21	-0.29	0.07	-0.20	0.04	1.00			
7	**ParentBrand**[a]	129.06	17.57	0.00	0.26	0.26	-0.04	0.05	-0.58	1.00		
8	**Body Style**	0.50	0.50	-0.61	-0.32	0.08	-0.18	-0.05	0.00	0.29	1.00	
9	**Seasonality**	0.33	0.47	-0.01	0.01	-0.09	0.04	-0.01	0.00	-0.01	0.00	1.00

Note:

[a] For IQS code, higher scores on parent brand quality imply lower quality.

[b]T-S synergy after residual regression.

Table 9 Principal components of traditional and social media for new and established products

Variables	**Eigenvectors**	
	New products	Established products
Traditional media		
Broadcast media, β_1	0.538	0.482
Print media, β_1	0.567	0.611
Broadcast-print media synergy, β_3	0.623	0.628
Social media		
Online consumer review, γ_1	0.436	0.232
Blog, γ_2	0.612	0.658
Review-blog synergy, γ_3	0.66	0.716

Table 10 SUR estimation results for new and established products

	Estimates (New product sales model)	**Estimates** (established products)	
		Customer acquisition model	Customer retention model
Product performance equation			
Intercept	**4.849*** (1.168)**	**8.918*** (0.616)**	**4.771*** (0.594)**
Traditional media factor	**0.027* (0.016)**	**0.049*** (0.006)**	**0.052*** (0.006)**
Social media factor	**0.119*** (0.021)**	**0.057*** (0.017)**	**0.049*** (0.017)**
Traditional-social media synergy	**-0.004** (0.002)**	0.004 (0.002)	**0.005** (0.002)**
Quality	0.262 (0.185)	**-0.429*** (0.101)**	**-0.353*** (0.096)**
Parent brand	**0.018*** (0.006)**	-0.004 (0.003)	0.003 (0.003)
Body style	**-1.163*** (0.141)**	**-0.885*** (0.076)**	**-0.450*** (0.073)**
Seasonality	0.122 (0.095)	0.033 (0.070)	0.081 (0.070)
R-square	*0.70*	*0.55*	*0.44*
Social media equation			
Intercept	-3.297 (8.166)	**10.93*** (1.937)**	**14.07*** (1.922)**
Traditional media factor	-0.086 (0.060)	**-0.121*** (0.022)**	**-0.118*** (0.022)**
Lagged DV	**0.899*** (0.222)**	**0.592*** (0.042)**	**0.488*** (0.044)**
Quality	1.373 (1.386)	-0.521 (0.349)	**-0.621* (0.352)**
Parent brand	0.033 (0.046)	-0.003 (0.009)	-0.006 (0.010)
Body style	0.156 (0.084)	-0.022 (0.266)	-0.329 (0.226)
R-square	*0.27*	*0.21*	*0.20*

*p<0.10, **p<0.05, ***p<0.01

Notes: Coefficient (SE)

Table 11 Principal components of traditional and social media for established products (Yearly results)

Variables	**Eigenvectors**		
	2007	***2008***	***2009***
Established products: Traditional media			
Broadcast media, β_1^Y	0.498	0.386	0.254
Print media, β_1^Y	0.587	0.644	0.68
Broadcast-print media synergy, β_3^Y	0.637	0.66	0.687
Established products: Social media			
Online consumer review, γ_1^Y	0.187	0.474	0.5
Blog, γ_2^Y	0.684	0.565	0.539
Review-blog synergy, γ_3^Y	0.705	0.676	0.677

Table 12 Yearly SUR estimation results for established products

	Estimates(2007)	**Estimates(2008)**	**Estimates(2009)**
Customer acquisition for established products equation			
Intercept	**10.73*** (0.538)**	**9.11***(1.418)**	**10.58** (1.174)**
Traditional media factor	**0.017** (0.005)**	0.013 (0.010)	**0.067* (0.035)**
Social media factor	**0.052*** (0.010)**	**0.116** (0.042)**	**0.081* (0.048)**
Traditional-social media synergy	-0.0003 (0.003)	**0.009* (0.005)**	-0.028 (0.029)
Quality	**-0.653*** (0.102)**	-0.167 (0.222)	**-0.306** (0.151)**
Parent brand	**-0.010*** (0.003)**	**-0.014*** (0.005)**	**-0.025*** (0.007)**
Body style	**-0.572*** (0.069)**	**-0.957*** (0.111)**	**-0.649*** (0.161)**
Seasonality	0.036 (0.054)	0.019 (0.092)	-0.187 (0.125)
R-square	*0.75*	*0.73*	*0.56*
Social media for established products equation			
Intercept	**-32.77*** (6.252)**	**23.53*** (2.327)**	**4.531** (2.443)**
Traditional media factor	**-0.093** (0.045)**	**-0.095*** (0.027)**	**0.149* (0.080)**
Lagged customer acquisition	**3.782*** (0.421)**	**0.361*** (0.093)**	**0.395*** (0.371)**
Quality	**2.364** (0.865)**	**-3.383*** (0.414)**	0.005 (0.323)
Parent brand	**0.058** (0.020)**	**-0.036** (0.011)**	**0.048** (0.015)**
Body style	**1.457** (0.095)**	**0.618** (0.296)**	**-1.017** (0.322)**
R-square 0.42 0.63 0.36			

*p<0.10, **p<0.05, ***p<0.01

Notes: Coefficient (SE)

	Estimates(2007)	**Estimates(2008)**	**Estimates(2009)**
Customer retention for established products equation			
Intercept	**5.668^{***} (0.703)**	**5.026^{**} (1.564)**	**6.767^{***} (1.023)**
Traditional media factor	**0.033^{***} (0.007)**	**0.032^{**} (0.011)**	**0.085^{**} (0.033)**
Social media factor	**0.041^{**} (0.015)**	**0.086^{**} (0.047)**	0.035 (0.046)
Traditional-social media synergy	-0.001 (0.004)	0.007 (0.005)	-0.044 (0.028)
Quality	**-0.571^{***} (0.135)**	-0.313 (0.242)	-0.213 (0.130)
Parent brand	0.003 (0.003)	-0.001 (0.005)	**-0.018^{**} (0.006)**
Body style	**-0.395^{***} (0.091)**	**-0.524^{***} (0.119)**	-0.195 (0.141)
Seasonality	0.103 (0.079)	0.040 (0.104)	0.017 (0.018)
R-square	*0.54*	*0.45*	*0.38*
Social media for established products equation			
Intercept	-3.893 (5.582)	**26.34^{***} (2.187)**	**7.562^{***} (2.458)**
Traditional media factor	**-0.093^{*} (0.053)**	**-0.097^{**} (0.028)**	**0.153^{*} (0.083)**
Lagged customer retention	**2.216^{***} (0.419)**	**0.215^{**} (0.097)**	**0.209^{**} (0.084)**
Quality	1.095 (0.981)	**-3.461^{***} (0.422)**	-0.080 (0.334)
Parent brand	0.019 (0.024)	**-0.042^{***} (0.011)**	**0.042^{**} (0.015)**
Body style	0.026 (0.659)	0.384 (0.291)	**-1.285^{***} (0.328)**
R-square 0.21 0.61 0.32			

*p<0.10, **p<0.05, ***p<0.01.

Notes: Coefficient (SE)

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