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The Product and Timing Effects of eWOM in Viral Marketing

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ABSTRACT

To be effective in viral marketing campaign, firms must first select proper disseminators, and then use them as opinion leaders to communicate product information with followers via mass media in the online space. In this paper, we study major characteristics of opinion leaders and find that their online word-of-mouth (eWOM) increase product sales. Our findings provide firms managerial insights about product aspects of eWOM, and how firms should arrange the timing of eWOM for successful viral marketing campaign.

JEL Classifications: M00, M1, M3

Keywords: viral marketing; opinion leaders; eWOM; product effect; timing effect

I. INTRODUCTION

Word of mouth (WOM) has long been used to promote products or to criticize competitors (Jacobson, 1948; Katz and Lazarsfeld, 1955). Its impact on sales and diffusion of new products was first reported to be positive in Arndt's (1967) study. In recent years, the development of social network and social media has further helped the spread of WOM via the Internet. Thus eWOM has been suggested as "free sales assistant" of online sellers (Chen and Xie, 2008). It is critical for firms to identify proper opinion leaders for seeding eWOM in order to generate favorable buzz effectively towards their products.

It has been noted that consumers have shown a tendency of using eWOM in finalizing their buying decisions (Guernsey, 2000). Studies have revealed that consumers tend to consult with eWOM more than advertising because they trust their peers more than firms that sell products (Bao and Chang, 2014b; Piller, 1999). Thus, firms that receive favorable eWOM will likely enjoy a better chance for sales increase (Chevalier and Mayzlin, 2006; Chung, 2011). eWOM is an important source of information for consumers to make purchase decisions. Given the user-generated nature of eWOM, how can firms better utilize such eWOM to their advantage? As a hybrid between traditional advertising and consumer word of mouth, eWOM can be initiated by firms as a campaign and implemented by consumers for marketing communications (Godes and Mayzlin, 2009). For an eWOM marketing campaign to be successful, it is critical to consider the behavioral characteristics of target consumers and the seeding strategy for selecting opinion leaders (Hinz et al., 2011). The purpose of this study is to identify eWOM opinion leaders and to examine the product and timing effects of such opinion leaders' eWOM on product sales.

II. VIRAL MARKETING VIA OPINION LEADERS

In a viral marketing campaign, firms select a small number of consumers as opinion leaders to disseminate information (Hinz et al., 2011). To be effective in such campaign, firms must first identify key opinion leaders, and then let key opinion leaders to communicate the information with followers via mass media (Iyengar, Van den Bulte, and Valente, 2011). Key opinion leaders are consumers who provide information and leadership to others in making their consumption decisions (Childers, 1986). Given the opinion leaders' behavioral tendency and ability to influence purchase decisions of followers, a firm can benefit from effective use of such opinion leaders in order to assist potential customers for shaping their buying decisions in favor of the firm's products. A theoretical basis for viral marketing is the two-step interpersonal communication process that involves target opinion leaders (Lazarsfeld, Berelson, and Gaudet, 1948). For example, by using fashion-related magazines as a mass media, firms can benefit from the use of target opinion leaders in women's clothing fashion who tend to read such magazines (Summers, 1970). However, how can firms identify proper opinion leaders for effective viral marketing? Based on the nature of eWOM, we review the literature on opinion leader and WOM related to viral marketing and propose hypotheses for studying the relationships between opinion leaders' eWOM and sales.

Rogers and Cartano (1962) summarized three methods of identifying opinion leaders: (1) self-designation, i.e., asking consumers to identify whether and to which extent they are opinion leaders; (2) sociometric method, i.e., using social network to compute network centrality and other network structure related measures; (3) key informant method, i.e., asking consumers whom they listen to. The self-designation method seems to be the most popular method in marketing literature due to the survey proposed by King and Summers (1970), while the key informant method is also used in recent studies (Nair, Manchanda, and Bhatia, 2010). The main finding is that, self-designated and peer-nominated opinion leaders influence the choices of their followers. The sociometric method has been widely used by network analysis researchers, and has obtained increasing recognition among marketers (Hinz et al., 2011; Iyengar, Van den Bulte, and Valente, 2011). Previous studies reveal that both hub (that connects with many people) and bridge (that connects two clusters) are influential (Hinz et al. 2011). However, large cascade of influences may not be driven by opinion leaders but by a large number of easily influenced people (Watts and Dodds, 2007). In addition to the above-mentioned methods, other methods are also used to identify opinion leaders. For example, Aral and Walker (2012) use demographics to identify opinion leaders, and Godes and Mayzlin (2009) examine whether loyalty can be a moderating factor for self-designated opinion leaders.

In this study, we empirically examine the appropriateness of opinion leaders identified from a dataset of Amazon reviews for the benefit of using its product sales rank and user review information. The dataset is described in the following section. In order to classify key eWOM opinion leaders, we consider three attributes of Amazon website reviewers in the dataset (Bao and Chang, 2014a). The first attribute is how many reviews a consumer posts on the website. By counting the number of reviews a consumer writes, we identify communicative reviewers as opinion leaders. According to an early study (Lazarsfeld, Berelson, and Gaudet, 1948), communicative opinion leaders tend to be someone who is most concerned and most articulate about the products. Consumers send their opinions for a number of reasons. Based on their expertise and/or usage experience, opinion leaders have a tendency of helping other consumers or the firm (Sundaram, Mitra, and Webster, 1998). Posting reviews give them a chance to articulate their opinions and thus reduce the emotional tension if they feel strongly about a product (Dichter, 1966).

The second attribute of opinion leaders is how much buzz a consumer's review generates from peers. We identify buzz-generating consumers as opinion leaders. Previous study demonstrates that opinion leaders are progressive attention-seekers (Summers, 1970). Opinion leaders fulfill their self-enhancement motivation via buzz creation (Engel, Blackwell, and Miniard, 1993). The reviews written by buzz-generating opinion leaders can generate buzz among followers to increase product/brand awareness. And such awareness was found to be good for sales, whether the buzz is positive or negative (Berger, Sorensen, and Rasmussen, 2010). As such, buzz-generating opinion leaders could help firms to increase sales through the buzz they created.

The third attribute of opinion leaders is how trustworthy product reviews are considered by other consumers. In the offline world, WOM is spread through consumers who know each other, that is, "whom he knows" for an opinion leader (Katz, 1957). But this is not the case in an online setting where eWOM is disseminated freely among strangers. It remains a question why consumers trust eWOM from strangers? Obtaining target consumers' trust is a major challenge for firms operating on the Internet (Resnick and Zeckhauser, 2002). Consumers tend to rely on information sources with good reputation. Structural, lexical, semantical aspects of eWOM have been found to be related to trustworthiness of eWOM (Cao, Duan, and Gan, 2011; Bao, 2016). We identify the most trustworthy buzz-creating opinion leaders as the consumers who generate the most helpful reviews.

Having identified communicative, buzz-generating, and trustworthy opinion leaders, we study the relationships between sales and eWOM of these opinion leaders. We discuss two streams of research on eWOM that have been found in the literature, namely, product effects and timing effects.

III. HYPOTHESES

A. Product Effect of eWOM on Sales

There are three product aspects of eWOM, namely, product awareness/popularity, customer satisfaction and horizontal product differentiation. We first examine the product awareness/popularity of eWOM. Product awareness is the first phase in consumer's buying decision. Without product awareness, consumers will not have the interest and desire to consider a particular product that leads to a buying decision. The amount of eWOM influences consumers in two ways. It has been noted that the amount of eWOM increases exposure to a product and therefore increases consumer's awareness of the existence of a product (Liu, 2006). In addition, large amount of eWOM suggests popularity of a product (Chen, Wu, and Yoon, 2004; Zhu and Zhang, 2010). Previous studies reveal that volume of eWOM drives sales (Chevalier and Mayzlin, 2006; Duan, Gu, and Whinston, 2008; Liu, 2006). We thus propose:

H1a: Product Popularity and Awareness is positively associated with Sales.

Consumers communicate their satisfaction using online user rating (Chen and Xie, 2008; Sun, 2012). The persuasiveness of user review depends on consumption goal of a consumer. Positive review is more persuasive than negative review for products used for promotional consumption goal, while the opposite holds for products used for prevention consumption goal (Zhang, Craciun, and Shin, 2010). It has been found that consumer satisfaction can influence future sales (Kopalle and Lehmann, 2006; Yi, 1990). In his study, Liu (2006) indicates that positive rating can enhance consumer's attitude while negative rating reduces attitude. Although most existing literature finds that product satisfaction drives sales (Chevalier and Mayzlin, 2006; Chintagunta, Gopinath, and Venkataraman, 2010), negative review can also drive sales due to its ability to increase consumer awareness (Berger, Sorensen, and Rasmussen, 2010). Therefore, we propose:

H1b: Product Satisfaction is positively associated with Sales.

Consumers perceive vertical differentiation in the same way. In contrast, consumers have different rankings of a group of products which are horizontally differentiated (Hotelling, 1929). For example, fuel efficiency in mile per gallon (mpg) is vertical differentiation. But features of comfort vs. sportiness are examples of horizontal product differentiation. The same product can satisfy some consumers and receive high ratings while disappoint other consumers and receive low ratings at the same time. And a high variance indicates that a product is well differentiated horizontally, satisfying more consumers in different target segments, and therefore drives sales (Clemons, Gao, and Hitt, 2006; Godes and Mayzlin, 2004; Sun, 2012). We thus propose:

H1c: Horizontal Product Differentiation is positively associated with Sales.

B. Timing Effect of eWOM on Sales

It has been noted that eWOM marketing campaign tends to last a short period of time (Godes and Mayzlin, 2009). The timing of launching eWOM is thus critical for generating desired effect of a firm's marketing campaign. Researchers have found that eWOM at the early stage of product launch increases product sales (Liu 2006; Li and Hitt, 2008). However, eWOM has diminishing effects over time (Cao, Duan, and Gan, 2011). It is then a challenge for firms to decide how to arrange the timing of eWOM marketing campaign. Two hypotheses (H3a and H3b) are developed to test the relationships between the first arrival and time span of eWOM and sales. Finally, similar to advertising intensity, we hypothesize (H3c) that the intensity of eWOM also has an impact on sales (Appleton-Knapp, Bjork, and Wickens, 2005; Naik, Mantrala, and Sawyer, 1998; Strong, 1977). We use standard deviation of opinion leaders' eWOM as a proxy for eWOM intensity.

H2a: Early arrival of top eWOM is positively associated with sales.

H2b: Long time span of top eWOM is positively associated with sales.

H2c: High intensity of top eWOM is negatively associated with sales.

IV. DATA AND MODEL

A. Data and Opinion Leaders

Online user review has been used as a proxy for overall eWOM (Zhu and Zhang, 2010). In this paper, we use an Amazon user review dataset to identify opinion leaders and study eWOM dissemination. The dataset contains a sample of 350,122 book, music, video and DVD titles that, as experience goods, have qualities difficult to ascertain before consumption, and therefore user reviews are helpful for consumers (Nelson, 1970; Park and Lee, 2009). A user review on Amazon has both a star rating and a text review. For each title, we collect three statistics of star rating, i.e., average rating, number of reviews, and variance of all star ratings for the title. On average, a title receives 13.98 reviews with an average rating of 4.33 and variance of 0.68. Amazon puts each title into relevant product categories. Amazon product category has a tree structure. For example, Jane Austen's Sense and Sensibility belongs to the category: /Books/Literature and Fiction/World Literature/ British/19th Century. The category at the top level of the tree is book, and the deeper the tree is, the finer the category becomes. The category count for a title ranges from 1 to 116 with an average of 4.88. Our approach to identify opinion leaders is based on the fact that Amazon allows consumers to display their names for their user reviews. We identify 2,145,885 unique consumers in the dataset. On average, a unique consumer writes 4.37 reviews. The most prolific consumer writes 8,659 reviews. Amazon provides a mechanism for consumers to respond to a user review, that is, consumers can vote whether a user review is helpful or not. The number of votes (either helpful or not) that a user review receives is a proxy for buzz. And the number of helpful votes is a proxy for how trustworthy a user review is. On average, a consumer receives 26.43 votes, and 12.83 helpful votes.

Some researchers treat all reviewers as opinion leaders (Cui, Lui, and Guo, 2010). But we are interested in examining a much smaller set of reviewers because it is costly for a firm to recruit all available reviewers. The theoretical basis for considering a subset of reviewers is that opinion leadership is not a dichotomy: consumers are not clearly divided into two groups of opinion leader and followers. Instead, opinion leaders also listen to followers, and opinion leadership varies in a continuous fashion (Rogers, 1962). As discussed in Introduction, we identify communicative opinion leaders as the top 21,458 reviewers in terms of the number of user reviews written (1% of the total unique consumers in the dataset). By the same token, we can identify buzz-generating opinion leaders in terms of number of feedback votes, and identify trustworthy opinion leaders in terms of the number of helpful votes. It is worth noting that the three types of opinion leaders are not mutually exclusively. The overlapping of different types of opinion leaders is consistent with extant literature (Iyengar, Van den Bulte, and Valente, 2011).

B. Communicative Opinion Leader's eWOM

We discuss how to operationalize the hypothesis for communicative opinion leaders (the same operationalization applies to buzz-generating and trustworthy opinion leaders). Since we are interested in the impact of opinion leaders on sales, the unit of analysis is a title. Following extant literature, we use log transformation of sales rank as a proxy to sales (Chevalier and Mayzlin 2006). To test product effects of eWOM (H1a-c), we collect star ratings from communicative opinion leaders for each title. Then we compute the three statistics for each title, i.e., number of ratings (volume), average rating (valence), and standard deviation (SD). We operationalize product popularity/awareness, product satisfaction, and horizontal differentiation by volume, valence, SD (summary statistics of the variables for communicative opinion leaders are reported in Table 1). A title receives an average of 6.02 reviews from communicative opinion leaders, and the average rating is 4.24, and the standard deviation is 0.40.

To study timing effects of eWOM, we need a measure of when user reviews arrive. Since we do not have information on when a title is launched on Amazon, we use the date of the first user review as a proxy for the launch date. The arrival time of a user review is the days elapsed from the launch date. We collect arrival time of the first review written by a communicative opinion leader. We also collect the arrival time of all reviews by communicative opinion leaders, and use them to find the average and standard deviation of arrival times.

Table 1
Summary statistics

Variable	Mean	Std. Dev.
Log sales rank (Sales)	11.57	1.60
Category count ($Count_{cat}$)	5.34	4.95
Volume of reviews (Volume)	6.02	17.57
Average rating (Valence)	4.24	0.86
Std. dev. of rating (SD)	0.40	0.50
Arrival time of first review ($Time_1$)	454.70	562.48
Average arrival time of reviews ($Time_{ave}$)	758.80	634.58
Std. dev. of arrival time of reviews ($Time_{SD}$)	239.20	264.82

Table 2
Summary statistics for product group

	Book	Music	Video	DVD
Number	129615	46913	10725	12000

We add two control variables for each title. The first is the number of categories a title belongs to as category count. As shown in Table 1, a title belongs to 5.34 categories. The highest number is 116. As described in Data section, Amazon's category has a tree structure. We use the top level of category as a control variable and refer to it as group. A group can be book, music, video, and DVD (Table 2).

We specify the following model to empirically test our hypothesis.

$$\begin{aligned} Sales = {} & \beta_0 + \beta_1 group + \beta_2 count_{cat} + \beta_3 valence^j + \beta_4 volume^j \\ & + \beta_5 SD^j + \beta_6 time_1^j + \beta_7 time_{ave}^j + \beta_8 time_{SD}^j + \varepsilon \end{aligned} \tag{1}$$

where Sales = logarithm of sales rank; J = types of opinion leaders, i.e., communicative, buzz-generating, and trustworthy; Group = top level of category tree, i.e., book, music, DVD, and video; $Count_{cat}$ = number of categories to which a title belongs; $Valence^j$ = average review by type j opinion leader; $Volume^j$ = number of reviews by type j opinion leader; SD^j= standard deviation of reviews by type j opinion leader; $Time_1^j$= arrival time of first review by type j opinion leader; $Time_{ave}^j$= average arrival time of reviews by type j opinion leader; and $Time_{SD}^j$= standard deviation of arrival time of reviews by type j opinion leader.

V. RESULTS AND DISCUSSIONS

We first test our model specifications with the alternative model where timing effects is omitted. We conduct regression analysis on 90% of the total sample, and then use the estimated parameters to conduct a prediction exercise on the remaining 10% hold-out sample. Comparison of in-sample fit and prediction error on hold-out sample suggests that our model fit the sample better (Table 3). Next we report estimation results on communicative opinion leaders. Similar results hold for buzz-generating and trustworthy opinion leaders.

Table 3
Model validation

	In sample (AIC[b])	Hold-out sample (RMSE[c])
Model 1[a]	580977.700	3.086
Model 2	570920.200	3.054

[a] Model 1: product effects only; model 2: product and timing effects.
[b] Akaike's Information Criterion (AIC) is defined as $AIC = -2 \times \log(l) + 2 \times p$, where l is likelihood and p is number of parameters.
[c] RMSE = Root Mean Square Error.

Table 4
Estimates of eWOM of communicative opinion leaders

	Model 1 (product effects)	Model 2 (product and timing effects)
Intercept	13.472*	13.460*
	(0.017)	(0.017)
DVD (Group)	-2.207*	-2.262*
	(0.014)	(0.014)
Music (Group)	-1.269*	-1.291*
	(0.007)	(0.007)
Video (Group)	-2.532*	-2.510*
	(0.014)	(0.013)
Category count ($Count_{cat}$)	-0.018*	-0.013*
	(0.0007)	(0.0007)
Average rating (Valence)	-0.220*	-0.168*
	(0.004)	(0.004)
Volume of reviews (Volume)	-0.016*	-0.013*
	(0.0002)	(0.0002)
Std. dev. of rating (SD)	-0.520*	-0.255*
	(0.006)	(0.007)
Std. dev. of arrival time of reviews ($Time_{SD}$)		2.900e-04*
		(2.956e-05)
Average arrival time of reviews ($Time_{ave}$)		-1.007e-03*
		(2.094e-05)
Arrival time of first review ($Time_1$)		7.471e-04*
		(2.177e-05)
Model fit	0.4013	0.4337

*: significant at P-value less than 0.001. Standard Deviation is in bracket.

The intercept estimates in Table 4 is interpreted as the intercept for book group since group is a factor variable. The music group has a significant estimate of -1.291 where the minus sign implies that, as a group, music titles have higher sales than book titles because a lower sales rank means higher sales. Comparing estimates on music, video, and DVD, we find that video has the highest sales, DVD the second highest, music the third highest, and book the lowest. The estimate on category count is -0.013 and significant. It implies that sales increase in category count. An explanation is that category count is a proxy for content diversity of a title. The more diversified a content is, the more market segments a title appeals to, and thus the more consumers it is able to attract.

A. Product Effects of eWOM from Communicative Opinion Leaders

The estimate for volume is -0.013 and significant. It implies that high product popularity/awareness increases sales (H1a). The estimate for average rating is -0.168 and significant. It implies that high product satisfaction increases sales (H1b). The estimate for standard deviation is -0.255 and significant. It implies that high horizontal differentiation increases sales (H1c). Although the extant literature has demonstrated the three product effects, researchers have not found evidence that all three product effects are significant in one empirical setting. Explanations for the inconsistency are: (1) empirical issues including collinearity and functional form (Godes and Mayzlin, 2004), market aggregation and time series (Chintagunta, Gopinath, and Venkataraman, 2010), (2) specific roles of a measure including volume increasing awareness (Liu, 2006) and variance signaling hyper-differentiation (Clemons, Gao, and Hitt, 2006), and (3) variance and volume both depends on quality (Moe, 2009). Consumer satisfaction, consumer awareness/popularity, and horizontal differentiation are all costly to accomplish. The extent literature seems to suggest that marketers only need to focus on two of the three product effects. Our findings show the importance of improving all three product effects at the same time.

B. Timing Effects of eWOM from Communicative Opinion Leaders

The estimate of arrival time of the first review by communicative opinion leader is 7.471e-04 and significant. It implies that a short arrival time of the first communicative opinion leader's eWOM increases sales (H2a). But the estimate of average arrival time of all communicative opinion leaders is -1.007e-04 and significant. It implies that a long average arrival time of all communicative opinion leaders' eWOM increases sales (H2b). In addition, the estimate of standard deviation of all communicative opinion leaders is 2.900e-04 and significant. It implies that a small standard deviation of all communicative opinion leaders' eWOM increases sales (H2c).

Although prior studies have found evidence that opinion leaders and early purchasers can overlap, opinion leaders are not necessarily early purchasers (Arndt, 1967; Baumgarten, 1975). Recent studies in eWOM context have found that eWOM has more impact at the early stage of the product life cycle (Liu, 2006; Li and Hitt, 2008). So an implication is that firms should have eWOM marketing at the early stage of product launch. Our finding implies that opinion leader's eWOM has effects on sales at both early and later stage of product life cycle. In addition, a given eWOM has diminishing effects over time (Cao, Duan, and Gan, 2011). To arrange the timing of eWOM, firms should start eWOM of opinion leader as early as possible. But firms should also spread eWOM from opinion leaders over time. As a consequence, the average time will increase. The finding that small standard deviation of arrival time increases sales suggests that eWOM of opinion leaders should be close to one another. Such implication is consistent with the findings that advertising messages need to be grouped together to increase intensity in advertisement scheduling literature (Appleton-Knapp, Bjork, and Wickens, 2005; Naik, Mantrala, and Sawyer, 1998).

VI. CONCLUSION

In summary, our findings provide the following insights to help firms create communication campaigns in the US. Despite being a small fraction of target consumers, communicative, buzz-generating, and trustworthy opinion leaders drive sales by disseminating eWOM. Firms should start eWOM campaign as early as possible in order to obtain early mover advantage. But firms should not arrange all opinion leaders to write reviews at the early stage of the product adoption process. Instead, firms should have eWOM from opinion leaders over a long period of time. And eWOM intensity needs to be strong. This paper has the following limitations that we hope to address in the future research. First, we do not consider mediation factors such as willingness to buy and online-store image/product image. Second, the extant literature has identified opinion leaders based on network structure (Hinz et al. 2011). Our dataset does not have information to study the network-related properties of opinion leaders identified in our paper.

REFERENCES

Appleton-Knapp, S.L., R.A. Bjork, and T.D. Wickens, 2005, "Examining the Spacing Effect in Advertising: Encoding Variability, Retrieval Processes, and Their Interaction." *Journal of Consumer Research* 32 (2): 266–76.

Aral, S., and D. Walker, 2012, "Identifying Influential and Susceptible Members of Social Networks." *Science* 337 (6092): 337–41. doi:10.1126/science.1215842.

Arndt, J., 1967, "Role of Product-Related Conversations in the Diffusion of a New Product." *Journal of Marketing Research* 4 (3): 291–95.

Bao, T., 2016, "How Sender and Receiver Jointly Shape Message: An Empirical Study on Transactional Relationship in Electronic Word of Mouth." *International Journal of Internet Marketing and Advertising*.

Bao, T., and T.-L. S. Chang, 2014a, "Finding Disseminators via Electronic Word of Mouth Message for Effective Marketing Communications." *Decision Support Systems* 67 (November): 21–29. doi:10.1016/j.dss.2014.07.006.

Bao, T., and T.-L. S. Chang, 2014b, "Why Amazon Uses Both the New York Times Best Seller List and Customer Reviews: An Empirical Study of Multiplier Effects on Product Sales from Multiple Earned Media." *Decision Support Systems* 67 (November): 1–8. doi:10.1016/j.dss.2014.07.004.

Baumgarten, S.A., 1975, "The Innovative Communicator in the Diffusion Process." *Journal of Marketing Research* 12 (1): 12–18. doi:10.2307/3150653.

Berger, J., A.T. Sorensen, and S.J. Rasmussen, 2010, "Positive Effects of Negative Publicity: When Negative Reviews Increase Sales." *Marketing Science* 29 (5): 815–27.

Cao, Q., W. Duan, and Q. Gan, 2011, "Exploring Determinants of Voting for the 'helpfulness' of Online User Reviews: A Text Mining Approach." *Decision Support Systems* 50 (2): 511–21.

Chen, P., S.-Y. Wu, and J. Yoon, 2004, "The Impact of Online Recommendations and Consumer Feedback on Sales." In *Proceedings of the International Conference on Information Systems*, 711–24. Washington.

Chen, Y., and J. Xie, 2008, "Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix." *Management Science* 54 (3): 477–91.

Chevalier, J., and D. Mayzlin, 2006, "The Effect of Word of Mouth on Sales: Online Book Reviews." *Journal of Marketing Research* 43 (3): 345–54. doi:10.1509/jmkr.43.3.345.

Childers, T.L., 1986, "Assessment of the Psychometric Properties of an Opinion Leadership Scale." *Journal of Marketing Research*, 184–88.

Chintagunta, P., S. Gopinath, and S. Venkataraman, 2010, "The Effects of Online User Reviews on Movie Box Office Performance: Accounting for Sequential Rollout and Aggregation across Local Markets." *Marketing Science* 29 (5): 944–57.

Chung, J., 2011, "Investigating the Roles of Online Buzz for New Product Diffusion and Its Cross-Country Dynamics." *Journal of Business Research*, Innovation, Diffusion, and Adoption of High-Technology Products and Services, 64 (11): 1183–89. doi:10.1016/j.jbusres.2011.06.020.

Clemons, E., G. Gao, and L. Hitt, 2006, "When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry." *Journal of Management Information Systems* 23 (2): 149–71.

Cui, G., H.-K. Lui, and X. Guo, 2010, "Online Reviews as a Driver of New Product Sales." In *2010 Fourth International Conference on Management of E-Commerce and E-Government (ICMeCG)*, 20–25. doi:10.1109/ICMeCG.2010.13.

Dichter, E., 1966, "How Word-of-Mouth Advertising Works." *Harvard Business Review* 44 (6): 147–60.

Duan, W., B. Gu, and A. Whinston, 2008, "The Dynamics of Online Word-of-Mouth and Product sales—An Empirical Investigation of the Movie Industry." *Journal of Retailing* 84 (2): 233–42.

Engel, J.F, R.D. Blackwell, and P.W. Miniard, 1993, *Consumer Behavior*. Forth Worth: Dryden Press.

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

Godes, D., and D. Mayzlin, 2009. "Firm-Created Word-of-Mouth Communication: Evidence from A Field Test." *Marketing Science* 28 (4): 721–39. doi:10.1287/mksc.1080.0444.

Guernsey, L., 2000, "Suddenly, Everybody's An Expert." *The New York Times*, sec. Technology.http://www.nytimes.com/2000/02/03/technology/suddenly-everybody-s-an-expert.html.

Hinz, O., B. Skiera, C. Barrot, and J.U. Becker, 2011, "Seeding Strategies for Viral Marketing: An Empirical Comparison." *Journal of Marketing* 75 (6): 55–71.

Hotelling, H., 1929, "Stability in Competition." *Economic Journal* 39 (153): 41–57.

Iyengar, R., C. Van den Bulte, and T.W. Valente, 2011, "Opinion Leadership and Social Contagion in New Product Diffusion." *Marketing Science* 30 (2): 195–212.

Jacobson, D.J., 1948, *The Affairs of Dame Rumor*. Rinehart.

Katz, E., 1957, "The Two-Step Flow of Communication: An Up-To-Date Report on A Hypothesis." *Public Opinion Quarterly* 21 (1): 61–78. doi:10.1086/266687.

Katz, E., and P.F. Lazarsfeld, 1955, *Personal Influence: The Part Played by People in the Flow of Mass Communications*. Free Press.

King, C.W., and J.O. Summers, 1970, "Overlap of Opinion Leadership across Consumer Product Categories." *Journal of Marketing Research* 7 (1): 43–50.

Kopalle, P.K., and D.R. Lehmann, 2006, “Setting Quality Expectations When Entering a Market: What Should the Promise Be?” *Marketing Science* 25 (1): 8–24. doi:10.1287/mksc.1050.0122.

Lazarsfeld, P.F., B. Berelson, and H. Gaudet, 1948, *The People’s Choice: How the Voter Makes up His Mind in A Presidential Campaign*. Columbia University Press.

Liu, Y., 2006, “Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue.” *Journal of Marketing* 70 (3): 74–89.

Li, X., and L.M. Hitt, 2008, “Self-Selection and Information Role of Online Product Reviews.” *Information Systems Research* 19 (4): 456–74. doi:10.1287/isre.1070.0154.

Moe, W., 2009, “How Much Does a Good Product Rating Help a Bad Product? Modeling the Role of Product Quality in the Relationship between Online Consumer Ratings and Sales.” Working Paper, University Of Maryland College Park.

Naik, P.A., M.K. Mantrala, and A.G. Sawyer, 1998, “Planning Media Schedules in the Presence of Dynamic Advertising Quality.” *Marketing Science* 17 (3): 214–35.

Nair, H.S, P. Manchanda, and T. Bhatia, 2010, “Asymmetric Social Interactions in Physician Prescription Behavior: The Role of Opinion Leaders.” *Journal of Marketing Research* 47 (5): 883–95.

Nelson, P., 1970, “Information and Consumer Behavior.” *Journal of Political Economy* 78 (2): 311–29.

Park, C., and T.M. Lee, 2009, “Information Direction, Website Reputation and eWOM Effect: A Moderating Role of Product Type.” *Journal of Business Research* 62 (1): 61–67.

Piller, C., 1999, “Everyone Is a Critic in Cyberspace.” *Los Angeles Times*. http://articles.latimes.com/1999/dec/03/news/mn-40120.

Resnick, P., and R. Zeckhauser, 2002, “Trust among Strangers in Internet Transactions: Empirical Analysis of eBay’s Reputation System.” *Advances in Applied Microeconomics* 11: 127–57.

Rogers, E.M., 1962, “Diffusion of Innovations.” *Diffusion of Innovations.*

Rogers, E.M, and D.G. Cartano, 1962, “Methods of Measuring Opinion Leadership.” *Public Opinion Quarterly* 26 (3): 435–41.

Strong, E.C., 1977, “The Spacing and Timing of Advertising.” *Journal of Advertising Research* 17 (6): 25.

Summers, J.O., 1970, “The Identity of Women’s Clothing Fashion Opinion Leaders.” *Journal of Marketing Research* 7 (2): 178–85. doi:10.2307/3150106.

Sundaram, D.S., K. Mitra, and C. Webster, 1998, “Word-Of-Mouth Communications: A Motivational Analysis.” In *Advances in Consumer Research*, edited by Joseph W. Alba and J. Wesley Hutchinson, 527–31. 25.

Sun, M., 2012, “How Does the Variance of Product Ratings Matter?” *Management Science* 58 (4): 696–707.

Watts, D.J., and P.S. Dodds, 2007, “Influentials, Networks, and Public Opinion Formation.” *Journal of Consumer Research* 34 (4): 441–58. doi:10.1086/519140.

Yi, Y., 1990, “A Critical Review of Consumer Satisfaction.” *Review of Marketing* 4 (1): 68–123.

Zhang, J.Q., G. Craciun, and D. Shin, 2010, "When Does Electronic Word-of-Mouth Matter? A Study of Consumer Product Reviews." *Journal of Business Research* 63 (12): 1336–41. doi:10.1016/j.jbusres.2009.12.011.

Zhu, F., and X. Zhang, 2010, "Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics." *Journal of Marketing* 74 (2): 133–48.