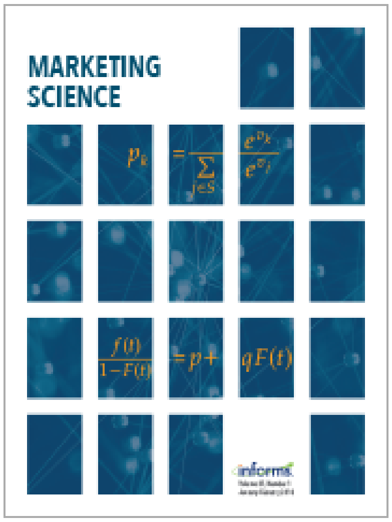

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An Empirical Study of Word-of-Mouth Generation and Consumption

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Word-of-mouth (WOM) plays an increasingly important role in shaping consumers' attitudes and buying behaviors. Prior work in marketing has mainly focused on the aggregate impact of WOM on product sales as well as the generation of WOM. Very little attention has been paid to the consumption or usage of WOM. In this paper, utilizing a unique data set that collects information from the automobile category on whether a consumer generates WOM to others and uses WOM for making purchase decisions, we build a discrete-choice model to study consumer WOM generation and WOM consumption decisions simultaneously and empirically answer questions that have not been explored previously. We are particularly interested in studying the key drivers of WOM generation/consumption and the synergy effect between the two WOM-related activities. We apply the proposed model to survey data collected on the automobile category. We find a strong synergy between WOM generation and WOM consumption. Although some consumers view WOM generation and WOM consumption as complementary to each other, others tend to perceive the two activities as competing with each other. We also find that consumer product experience and media exposure are positively correlated with their propensity to generate WOM. However, their effect on WOM consumption is mixed. Our empirical analysis also provides evidence of unobserved heterogeneity in the way consumer WOM activities are related to consumer product experience. Overall, these findings lead to important managerial implications on targeting for effective use of WOM as a marketing tool.

Key words: word-of-mouth; communication; discrete-choice model; probit model; finite mixture model
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Introduction

Word-of-mouth (WOM) has been frequently cited as the most effective form of communication in influencing consumers. This finding dates back to Katz and Lazarsfeld's seminal study in the 1940s, which found that word-of-mouth is at least twice as influential as the mass media (Katz and Lazarsfeld 1955, Engel et al. 1969, Herr et al. 1991). With the rapid growth of social networks, consumer evaluations and opinions of a product or service have become widely available. As a result, WOM plays an even more important role today in shaping consumers' attitudes and buying behaviors. According to the 2007 Nielsen Global Survey, 78% of people found "recommendations from consumers" is the form of advertising that they trust most. Some practitioners even argue that one single survey question can serve as a useful predictor of growth—that is, whether your customers are willing to recommend a product to others (Reichheld 2003).

For WOM to be effective, two processes need to work simultaneously: WOM generation (i.e., sending the information) and WOM consumption (i.e., using it for making purchase decisions). Prior work in marketing has mainly focused on the aggregate WOM impact on outcomes such as TV show ratings or product sales (Godes and Mayzlin 2004, Liu 2006) and the generation of WOM (Frenzen and Nakamoto 1993, Bowman and Narayandas 2001). Very little attention has been paid to WOM consumption or usage. However, WOM consumption plays an important role in facilitating the flow of information and affects product diffusion and sales. The ultimate success of WOM depends on a combination of factors related to both WOM generation and its use in purchase decisions. It is therefore crucial to understand the key drivers of WOM generation and WOM consumption.

It is also of interest for marketers to understand the interdependence/synergy effect between the two WOM-related activities, generation and consumption. This synergy effect could be positive, such that the utility from engaging in both WOM generation and WOM consumption is higher than the sum of utilities from generating or consuming WOM alone.[1] In other words, consumers may perceive the two WOM-related activities as complements. In such cases, generating WOM is more desirable when the individual also consumes it because of the possibility that WOM consumption helps the consumer accumulate knowledge and, hence, become more capable of generating WOM. Meanwhile, consuming WOM is more desirable when the individual also generates WOM, perhaps because the individual expects her own WOM generation to be reciprocated and she can enjoy more of her future WOM consumption. On the other hand, the synergy effect between WOM generation and WOM consumption could be negative such that the utility from engaging in both is lower than the sum of utilities from generating or consuming WOM alone. In other words, consumers could view the two WOM activities as partial substitutes. In such cases, consumers may perceive the two activities as competing for their social-cognitive capacity, in which participation in WOM generation (consumption) will reduce the participation in WOM consumption (generation).

It is important to understand such an interdependent relationship between WOM generation and WOM consumption. Holding the intensities of the WOM generation and WOM consumption activities constant, the probability of an individual both generating and consuming WOM is larger when there is a positive synergy than when there is a negative synergy. It is therefore desirable for firms to target those with high intensity of and positive synergy between the generation and consumption of WOM in their WOM campaign. Imagine a scenario in which a WOM consumer never passes her recommendations to others and a WOM generator never uses WOM in making her own purchase decision. A WOM campaign may not be as effective in generating a high reach of the marketing message. To the best of our knowledge, we are the first to formally examine such an interdependent relationship between WOM generation and WOM consumption.

In this paper, we utilize a unique survey-based data set on the automobile category to empirically answer the following questions that have not been previously explored: Is there any synergy between WOM consumption and WOM generation? If yes, what is the nature of such interdependence? Is the interdependence positive or negative? How do consumer product experience and media-usage habits affect the generation and consumption of WOM after controlling for interdependence between the two WOM activities? Are there any consumer segments associated with different consumer responses to WOM generation and consumption? What are the targeting implications for WOM campaigns?

We propose a discrete-choice model that jointly models consumer decisions on WOM generation and WOM consumption and accounts for the potential synergy effect between the two activities. We assume that the consumer jointly maximizes her utility from WOM generation and WOM consumption; that is, the observed decision outcome achieves the highest utility among the four possible outcomes: generates and consumes, generates but does not consume, consumes but does not generate, or neither generates nor consumes. The synergy effect appears in the joint utility when the consumer both generates and consumes WOM. We adopt a finite mixture specification to model the unobserved heterogeneity associated with consumer response to WOM generation, WOM consumption, and the synergy effect between the two.

We apply the proposed model to survey data collected on the automobile category. We find that there is a strong synergy between WOM generation and WOM consumption. Although the majority of consumers tend to perceive WOM generation and WOM consumption as complementary to each other (i.e., participation in one activity encourages participation in the other), some consumers tend to perceive the two activities as competing with each other (i.e., participation in one activity reduces participation in the other). We also find that consumer category experience and media exposure are positively correlated with their propensity to generate WOM; however, their effect on WOM consumption is mixed. Consumer product experience and media exposure can positively or negatively explain consumer propensity to consume WOM. Our empirical analysis also provides evidence of unobserved heterogeneity in the way WOM activities are related to consumer product experience. Overall, these findings lead to important managerial implications on targeting for effective use of WOM as a marketing tool. Our policy simulation

[1] "Utility" is used in the language of random utility models, not necessarily anything accruing to, or experienced by, consumers.

illustrates that different seeding strategies (by choosing which segment of consumers as seeds) will lead to different return on a WOM campaign.

The remainder of this paper is organized as follows. In the next section, we review the relevant literature and position our study relative to previous studies. We then develop the econometric model capturing the interdependence of WOM consumption and generation. We subsequently present an application of the proposed model to the automobile category and discuss the empirical results and implications of this research. Finally, we conclude the paper and point to some future research directions.

Literature Review and Conceptual Framework

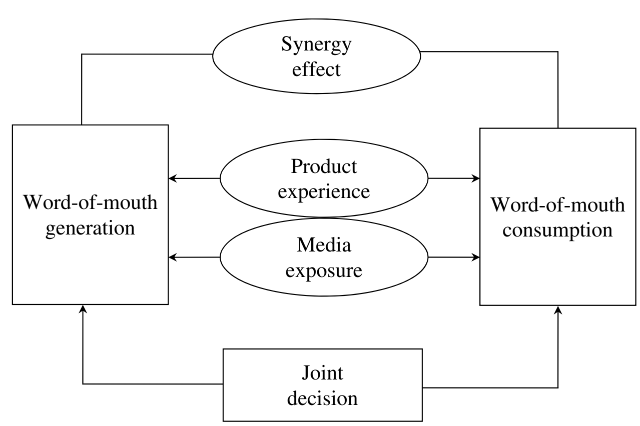
In the marketing literature, WOM usually refers to informal communications between private parties concerning evaluation of goods and services. Below, we provide a brief review on two streams of related literature in marketing and discuss how our study differs and extends the previous literature.

The first stream of literature studies the effect of WOM on measures of company performance such as customer satisfaction, customer loyalty, and future sales. In these studies, WOM is an antecedent or independent variable. For example, Nam et al. (2010) studied the effect of WOM on customer acquisition, retention, and usage for a new video-on-demand service and found that about 20% of new activations were due to WOM. There are many studies that have examined the relationship between product reviews and future product sales. The findings are mixed. Several studies have empirically shown that positive reviews are associated with higher sales, whereas negative reviews tend to hurt sales of experiential products like books and movies (Chevalier and Mayzlin 2006). Several other studies did not find a statistically significant relationship (Duan et al. 2005, Liu 2006). In addition, several studies have found that buyers seem to find movies and books that have generated a lot of reviews more interesting, thus driving more sales than those that have not received many comments (Dellarocas et al. 2005, Duan et al. 2005, Liu 2006). One concern with most of these studies is using reviews as a proxy of WOM and assuming consumers indeed read these product reviews. Unlike most of the aforementioned studies, we have survey data that directly measure consumer WOM generation and WOM consumption information.

The second stream of literature treats WOM as an outcome and studies the drivers of WOM activity. One line of research in this stream looks at the impact of social structure on WOM. Findings indicate that not all WOM is created equal, as its impact depends on who is talking to whom. Another line of research looks at what factors influence WOM generation behavior. For example, Anderson (1998) proposed a model to study the relationship between customer satisfaction and WOM. He found a U-shaped relationship in that both very low and very high levels of satisfaction generate WOM. Bowman and Narayandas (2001) used a binary-logit model to study customers' decisions on whether to tell anyone about their experience and a right-censored, truncated-at-zero negative binomial distribution model for studying the intensity of the WOM generation measured by how many people were told. Our study differs from previous research by modeling consumer simultaneous decisions of WOM generation and WOM consumption while capturing the synergy effect between the two. Figure 1 presents the conceptual framework of our study, which summarizes our key positioning.

Consumer product experience can play an important role in explaining consumer reactions to WOM. More product experience can signal two things. One is that the person has more knowledge about the product category. The other is that the product is more relevant or important to this person, such that the consumer has a higher interest in the product category. On the generation side, the more product experience the consumer has, the more knowledgeable the consumer is (thus the more trustworthy his or her WOM would be) and the more interest the consumer has in the product, thus leading to a higher likelihood for the person to generate WOM in this product category. On the consumption side, previous literature on information searches suggests mixed predictions. On the one hand, some authors found a negative relationship between product experience and information search (e.g., Anderson et al. 1979). Thus, more knowledge could reduce the consumer need for WOM and reduce the likelihood for a consumer to use WOM to help make purchase decisions. On the other hand, more knowledge, and higher relevance or

Figure 1 **The Conceptual Framework**



product interest, could lead to more WOM consumption. A few studies on consumer behavior show that prior knowledge encourages an information search by allowing the individual to form more questions and help her evaluate the responses to those questions, thus reducing the cognitive cost of using information and increasing the benefit of obtaining information (e.g., Jacoby et al. 1978).

Consumer media exposure levels can also affect how consumers react to WOM. For example, if a person watches TV or uses other media frequently, he or she may have more knowledge about the product category, and hence the need for WOM consumption (generation) is decreased (increased). In the case of generation, there is more information to send. In the case of consumption, there may be an information substitution effect; i.e., the information from media replaces the need for information from WOM. Therefore, we predict that the consumer media exposure level is negatively (positively) associated with the consumer likelihood of WOM consumption (generation) in that category.

We also hypothesize that there is a synergy effect between WOM generation and WOM consumption after controlling for consumer product experience, media exposure, and unobservable factors. In the case of positive synergy, WOM generation and WOM consumption will reinforce each other, whereas in the case of negative synergy, WOM generation and WOM consumption will undermine each other. Prior research suggests that opinion leadership is associated with opinion seeking (Katz and Lazarsfeld 1955, Wright and Cantor 1967), which may suggest a synergy effect between WOM generation and WOM consumption. However, to our knowledge, no prior studies have formally tested this relationship.

The Proposed Model

We observe information on whether consumer i generates WOM to others (WOM generation, $Y_i^G = 1$ or 0) and whether consumer i uses WOM in making a buying decision (WOM consumption, $Y_i^C = 1$ or 0) for the same product category. We observe four outcomes: (1) consumer generates and consumes WOM ($Y_i^G = 1$, $Y_i^C = 1$), (2) consumer generates but does not consume WOM ($Y_i^G = 1$, $Y_i^C = 0$), (3) consumer consumes but does not generate WOM ($Y_i^G = 0$, $Y_i^C = 1$), and (4) consumer neither generates nor consumes WOM ($Y_i^G = 0$, $Y_i^C = 0$).

We assume that the individual maximizes the joint utility from WOM generation and consumption because WOM generation and consumption are two important activities related to an individual's social tendency with respect to information. This connection may suggest a process for consumers to make a joint decision on whether to generate WOM and whether to consume. The joint utility of WOM generation and WOM consumption is specified as follows:

$$U(Y_i^G, Y_i^C) = (X_i\beta^G)Y_i^G + (X_i\beta^C)Y_i^C + \theta Y_i^G Y_i^C + \varepsilon(Y_i^G, Y_i^C). \qquad (1)$$

The basic intuition of Equation (1) is that $X_i\beta^G$ captures the intrinsic utility from WOM generation, $X_i\beta^C$ captures the intrinsic utility from WOM consumption, and θ captures the extrinsic utility from doing both. The joint utilities associated with the four outcomes for person i are

$$U(Y_i^G = 1, Y_i^C = 1) = X_i\beta^G + X_i\beta^C + \theta + \varepsilon_{i1}, \qquad (2a)$$

$$U(Y_i^G = 1, Y_i^C = 0) = X_i\beta^G + \varepsilon_{i2}, \qquad (2b)$$

$$U(Y_i^G = 0, Y_i^C = 1) = X_i\beta^C + \varepsilon_{i3}, \qquad (2c)$$

$$U(Y_i^G = 0, Y_i^C = 0) = \varepsilon_{i4}, \qquad (2d)$$

where X_i includes an intercept, a vector of variables measuring consumer i's product category experience, and a vector of variables measuring consumer i's media exposure. θ measures the synergy effect between WOM generation and WOM consumption, and εs are the error terms associated with the four decision outcomes to capture the random noise. The proposed model boils down to a multinomial-probit model when we assume the error terms to be distributed as multivariate normal:

$$\begin{bmatrix} \varepsilon_{i1} - \varepsilon_{i4} \\ \varepsilon_{i2} - \varepsilon_{i4} \\ \varepsilon_{i3} - \varepsilon_{i4} \end{bmatrix} \sim \text{MVN}\left(\mu = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \Sigma = \begin{bmatrix} 1 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{bmatrix}\right). \qquad (3)$$

We next show how we can identify the synergy effect θ. Equations (2a)–(2d) can be rewritten as follows, where β_0^G is the intercept of the utility of WOM generation and β_0^C is the intercept of the utility of WOM consumption:

$$U(Y_i^G = 1, Y_i^C = 1) = \beta_0^G + \beta_0^C + \theta + X_i\beta^G + X_i\beta^C + \varepsilon_{i1}, \qquad (4a)$$

$$U(Y_i^G = 1, Y_i^C = 0) = \beta_0^G + X_i\beta^G + \varepsilon_{i2}, \qquad (4b)$$

$$U(Y_i^G = 0, Y_i^C = 1) = \beta_0^C + X_i\beta^C + \varepsilon_{i3}, \qquad (4c)$$

$$U(Y_i^G = 0, Y_i^C = 0) = \varepsilon_{i4}. \qquad (4d)$$

Now X_i only includes a vector of variables measuring consumer i's product experience and a vector of variables measuring consumer i's media exposure. Because we have four possible decision outcomes, we are able to identify three intercepts in the multinomial discrete-choice model setting. In other words, we set the option of neither WOM generation nor WOM consumption as the baseline, whose mean utility is set to 0. Observations of $(Y_i^G = 1,\ Y_i^C = 0)$ allow us to identify the intercept of the WOM generation utility in Equation (4b), β_0^G. Similarly, observations of $(Y_i^G = 0, Y_i^C = 1)$ allow us to identify the intercept of the WOM consumption utility in Equation (4c), β_0^C. Finally, observations of $(Y_i^G = 1,\ Y_i^C = 1)$ allow us to identify the intercept in the joint utility of WOM generation and WOM consumption in Equation (4a), which is the sum of $\beta_0^G \beta_0^C$ and θ. Given that β_0^G and β_0^C are uniquely identified through Equations (4b) and (4c), the synergy measure θ can be uniquely identified through Equation (4a).

Let $P_i(Y_i^G, Y_i^C)$ denote the probability of observing person i's decision on WOM generation and WOM consumption. We can write down the probability of observing individual i's observed decision outcome as

$$f_i = P_i(1,1)^{Y_i^G Y_i^C} P_i(1,0)^{Y_i^G(1-Y_i^C)} \cdot P_i(0,1)^{(1-Y_i^G)Y_i^C} P_i(0,0)^{(1-Y_i^G)(1-Y_i^C)}. \tag{5}$$

Because we cannot obtain the closed form of $P_i(Y_i^G, Y_i^C)$, we approximate it using the Geweke–Hajivassiliou–Keane (GHK) simulator.

It is likely that the response of WOM generation and WOM consumption with respect to product experience and media exposure is different across consumers. To account for such unobserved consumer heterogeneity, we adopt the finite mixture specification[2] to assume that consumer i's observed decision follows a mixture of distributions, where f_{is} stands for the probability of observing i's decision if i belongs to segment s and m_{is} takes the logit form measuring the probability of i belonging to segment s. We allow the segment membership to be dependent on consumer demographics:

$$f_i = \sum_{s=1}^{S} m_{is} f_{is}(Y_i^G, Y_i^C \mid \beta_s^G, \beta_s^C, \beta_{0s}^G, \beta_{0s}^C, \theta_s, \Sigma_s), \tag{6}$$

$$m_{is} = \frac{\exp(\gamma_{s0} + \gamma_{s1}' demo_i)}{\sum_{k=1}^{S} \exp(\gamma_{k0} + \gamma_{k1}' demo_i)}. \tag{7}$$

We can then write down the log-likelihood function as

$$L(\beta_s^G, \beta_s^C, \beta_{0s}^G, \beta_{0s}^C, \theta_s, \gamma_s, \Sigma_s) = \sum_i \ln(f_i). \tag{8}$$

In our empirical application, we used the quasi-Newton method to maximize the log-likelihood function. The BHHH algorithm (Berndt et al. 1974) is employed to approximate the Hessian matrix.

[2] Please refer to Wedel et al. (1993) and Wedel and Kamakura (2000) for applications of the finite mixture model on cross-sectional data.

Empirical Analysis

In this section, we first present the data, model estimation, and empirical findings. We then conduct robustness checks for the potential sample-selection bias and endogeneity. We finally discuss the managerial implications.

Data and Model Estimation

We obtained cross-sectional survey data from a leading marketing research company that collects information in Great Britain on consumer buying behavior and attitudes. We have information on the automobile category from 2007. For those 4,544 respondents who had purchased a car in the past 12 months (new or used), the survey asked whether they used WOM in making purchase decisions (consumption) and whether they passed WOM to other people (generation). *WOM consumption* is a binary variable measuring whether the person used any WOM in making a purchase. *WOM generation* is also a binary variable measuring whether the person generates any WOM to her friends. The WOM can include consumer experience with the brand or product features. We find that the probability of WOM generation (0.66) is much higher than the probability of WOM consumption (0.24). Among the 4,544 respondents, about 18% generate and consume WOM, and 28% do neither. About 48% of the respondents generate but do not consume WOM, whereas only 6% of them consume but do not generate WOM. The correlation between *WOM generation* and *WOM consumption* is positive (0.125, p-value < 0.00), which sheds some light on the synergy effect between the two.

In addition, we have information on respondent product experience, media exposure, demographics, and where the respondent bought his or her car (channel).[3] For product experience, we have variables such as whether the respondent is a first-time buyer (*first time*), the annual mileage consumed (*mileage*), and the number of cars owned before (*quantity*). We have information on consumer media usage for print, television, and the Internet. Consumer demographics include gender, age, education, income, and marital status. Finally, we also observe whether the respondent purchased the car at a dealer (*shop*) or via other venues. The definitions of these variables are provided in Table 1. The summary statistics are reported in Table 2.

The data are cross-sectional, which is a limitation. However, they are unique and valuable in two ways. First, they provide information on both WOM generation and WOM consumption for the same individual.

[3] Unfortunately, we do not have information on the specific brands of cars that the consumers own. This would obviously be helpful in determining the amount of information consumers currently have about a brand and thus affect the benefit from consuming WOM.

Table 1 Variable Definitions

Variable type	Variable	Definition	Measures
WOM generation	*WOM generation*	Whether passed WOM to others	Yes = 1, no = 0
WOM consumption	*WOM consumption*	Whether used WOM in purchase decision	Yes = 1, no = 0
Product experience	*First time*	Whether the product is the first bought	Yes = 1, no = 0
	Mileage	Average annual mileage driven	1 = None 2 = 2,000 or less 3 = 2,001–4,000 4 = 4,001–6,000 5 = 6,001–9,000 6 = 9,001–12,500 7 = 12,501–20,000 8 = 20,001–30,000 9 = 30,001–40,000 10 = 40,001 or above
	Quantity	Number of items owned in that category	The actual number
Media exposure	*Print*	Frequency of reading newspapers and magazines	1 = None 2 = Quintile 5 (lowest) 3 = Quintile 4 4 = Quintile 3 5 = Quintile 2 6 = Quintile 1 (highest)
	Television	Frequency of watching TV	The same as above
	Internet	Frequency of using Internet	The same as above
Demographics	*Gender*	Gender	Male = 1, female = 0
	Age	Age	Actual age/10
	Education	Highest level of education achieved	1 = No formal schooling/incomplete primary education 2 = Primary education completed 3 = A few years of secondary education 4 = Completed secondary education 5 = High school education completed 6 = Further qualification (between high school and university) 7 = University degree 8 = Doctorate level or professional equivalent
	Income	Family income level	1 = Up to £9,999 2 = £10,000–£16,999 3 = £17,000–£22,999 4 = £23,000–£29,999 5 = £30,000–£39,999 6 = £40,000–£49,999 7 = £50,000+
	Married	Marital status	Married = 1, single = 0
Channel	*Shop*	Whether bought the product at a dealer	Yes = 1, no = 0

Notes. We used the linearization specification on all multiple-level categorical predictors rather than a dummy-coding specification to avoid estimating too many additional parameters. Our robustness check shows that the linearization specification does not lead to any substantive differences in the results.

This is unique because other databases collect information on either WOM generation or WOM consumption, but often not on both. Second, our data source provides an accurate measure on WOM consumption (i.e., whether the respondent utilizes WOM in making purchase decisions). Many prior studies have studied the relationship of product reviews and aggregate sales at the aggregate level. However, such a measure for WOM consumption is not as accurate.

We explored several variants of the proposed model based on the following specifications: (1) the proposed model in which we assume consumer maximization of the joint utility from WOM generation and WOM consumption versus a bivariate-probit model in which we treat WOM generation and WOM consumption as two binary decisions, (2) incorporating the synergy effect versus assuming it to be 0, (3) assuming the number of latent segments to be 1 (without unobserved heterogeneity) versus more than 1 (with unobserved heterogeneity), (4) assuming the synergy effect to be θ or θX_i, and (5) whether the unobserved heterogeneity applies

Table 2 Summary Statistics

Variable type	Variable	Mean	S.D.
WOM generation	*WOM generation*	0.658	0.474
WOM consumption	*WOM consumption*	0.241	0.427
	$Y^G = 1$, $Y^C = 1$	0.179	0.419
	$Y^G = 1$, $Y^C = 0$	0.479	0.261
	$Y^G = 0$, $Y^C = 1$	0.061	0.496
	$Y^G = 0$, $Y^C = 0$	0.281	0.439
Product experience	*First time*	0.071	0.257
	Mileage	3.944	2.473
	Quantity	1.426	0.749
Media exposure	*Print*	3.245	1.343
	Television	4.011	1.414
	Internet	3.205	1.737
Demographics	*Gender*	0.484	0.500
	Age	3.417	1.625
	Education	5.097	1.515
	Income	3.770	1.823
	Married	0.696	0.460
Channel	*Shop*	0.530	0.499

to the response coefficients of category experience, the response coefficients of media exposure, and the synergy effect. Our estimation results show that the following specification leads to the best model fit: incorporating the synergy effect θ, incorporating two latent segments with different intercepts, applying response coefficients to the product experience and the synergy effect, and incorporating one common variance–covariance matrix for the two segments.[4]

Estimation Results

We first discuss our findings on WOM generation (see Table 3). Overall, we find that consumers in the first segment have a significantly higher baseline WOM-generation propensity than consumers in the second segment. Consistent with our expectation, consumer-product experience is positively correlated with their WOM-generation propensity. However, the two segments show different patterns. In the first segment, we find that consumers with more driving experience are more likely to generate WOM. In the second segment, we find that first-time buyers are less likely to generate WOM. Confirming our expectation, we find that WOM generation is positively correlated with consumer media exposure. Specifically, consumers who read newspapers or magazines more often and consumers who spend more time browsing the Internet are more likely to generate WOM. Finally, we find

[4] Findings from our proposed model are robust to alternative specifications discussed in the paper. We report the Bayesian information criterion of some key benchmark models: the bivariate probit model with one-segment specification (10,163.29), proposed model with synergy effect and one-segment specification (10,111.71), proposed model with synergy effect and two-segment specification (10,097.91), and proposed model with synergy effect and three-segment specification (10,151.95).

Table 3 Estimates in the WOM Generation Equation

		Segment 1		Segment 2	
Variable type	Variable	Estimate	S.E.	Estimate	S.E.
	Intercept	**−1.767**	0.282	**−2.967**	0.278
Experience	*First time*	0.209	0.217	**−0.702**	0.201
	Mileage	**0.376**	0.076	0.038	0.058
	Quantity	**0.371**	0.094	0.044	0.184
Media exposure	*Print*	**0.078**	0.032	Tested to be the same as the other segment	
	Television	0.036	0.030		
	Internet	**0.144**	0.034		
Channel	*Shop*	**1.016**	0.213	**0.958**	0.372

Note. Bold estimates are the ones that are significant at the 5% level.

that consumers who purchased their cars through dealers are more likely to generate WOM compared with those who purchased their cars through other venues.

We next turn to WOM consumption activity (see Table 4). Overall, we find that consumers in the first segment have a significantly higher baseline WOM consumption propensity than consumers in the second segment. On the effect of consumer product experience, we find that first-time buyers in both segments are more likely to consume WOM, which is consistent with the hypothesis that limited product knowledge may generate a stronger consumer need for WOM to help them make purchase decisions. In the first segment, we find that mileage (capturing the person's driving experience) has a positive effect on WOM consumption, suggesting that more product experience makes it easier to process new information and may also signal a higher consumer interest in the product, thus leading to a higher propensity to information search and WOM consumption. For the effect of media exposure, we obtain some mixed findings. As predicted, we find that TV-viewing frequency is negatively correlated with WOM consumption. However, we find a positive relationship between Internet usage and WOM consumption. This could be due to the Internet's interactive environment and

Table 4 Estimates in the WOM Consumption Equation

		Segment 1		Segment 2	
Variable type	Variable	Estimate	S.E.	Estimate	S.E.
	Intercept	**−2.216**	0.408	**−4.008**	0.458
Experience	*First time*	**1.503**	0.310	**1.210**	0.480
	Mileage	**0.105**	0.046	0.151	0.086
	Quantity	−0.062	0.139	0.341	0.247
Media exposure	*Print*	0.011	0.051	Tested to be the same as the other segment	
	Television	**−0.125**	0.054		
	Internet	**0.264**	0.043		
Channel	*Shop*	**−1.567**	0.225	−0.607	0.342

Note. Bold estimates are the ones that are significant at the 5% level.

Table 5 Estimate of the Synergy Effect

Variable	Estimate	S.E.
Segment 1	**0.823**	0.200
Segment 2	−**1.255**	0.023

Note. Bold estimates are the ones that are significant at the 5% level.

the rapid development of online social communities where WOM in the form of product reviews and recommendations is widely available, therefore increasing consumer likelihood of WOM consumption. Finally, in the first segment, we find that those who purchased their cars through a dealer are less likely to consume WOM compared with those who purchased their cars through other venues.

An interesting finding from our analysis is the detection of the synergy effect between WOM generation and WOM consumption (see Table 5). Our empirical analysis suggests the existence of two segments of consumers; interestingly, these two segments show different patterns on the synergy effect. In the first segment, the interdependence between WOM generation and WOM consumption is positive, suggesting that the two activities are perceived to be complementary and that the utility of engaging in both activities is higher than the sum of the utility of engaging in one alone. For the second segment, the interdependence between WOM generation and WOM consumption is negative. This suggests that for these consumers, the two activities are perceived to be partial substitutes because the utility of engaging in both activities is lower than the sum of the utility of engaging in one alone.

Table 6 reports the variance–covariance matrix associated with the utilities of generating and consuming WOM, generating but without consuming WOM, and consuming but without generating WOM relative to the baseline utility of neither generating nor consuming WOM. The estimates reveal some significant covariance across these activities due to unobservables. Table 7 reports the prior segment membership estimates. We find that demographics are strong predictors. Males, younger consumers, more educated consumers, and consumers with higher pay

Table 6 Estimates of the Variance–Covariance Matrix

Variance–covariance matrix	Estimate	S.E.
σ_1^2	Fixed to be 1	N.A.
σ_2^2	**13.151**	1.987
σ_3^2	**8.489**	0.327
σ_{12}	−**0.520**	0.222
σ_{13}	−0.249	0.222
σ_{23}	**10.322**	1.144

Note. Bold estimates are the ones that are significant at the 5% level.

Table 7 Estimates in the Segment Membership Equation

Variable	Estimate	S.E.
Intercept	**0.875**	0.242
Gender	**0.322**	0.087
Age	−**0.162**	0.029
Education	**0.066**	0.030
Income	**0.078**	0.026
Married	−0.019	0.096

Note. Bold estimates are the ones that are significant at the 5% level.

are more likely to belong to the first segment (the more active one with a higher baseline WOM generation/consumption and a positive synergy effect).

To show the importance of modeling WOM generation and WOM consumption as a joint decision, and capturing the synergy effect between the two, we compared the parameter estimates from the synergy model (without segmentation) and their counterparts from a simple bivariate-probit model where we treat *WOM generation* and *WOM consumption* as two dependent variables. Note that for convenience of comparison, we performed an aggregate analysis without the finite mixture specification. As shown in Table 8, the bivariate-probit model leads to some overestimation

Table 8 Comparison of Model Estimates

		Bivariate-probit model		Synergy model one-segment	
Variable	Variable	Estimate	S.E.	Estimate	S.E.
WOM generation					
	Intercept	−**1.127**	0.015	−**0.466**	0.115
Product experience	*First time*	0.092	0.079	−0.019	0.051
	Mileage	**0.103**	0.010	**0.054**	0.009
	Quantity	**0.179**	0.032	**0.094**	0.021
Media exposure	*Print*	−0.013	0.013	**0.028**	0.009
	Television	−0.013	0.015	0.000	0.009
	Internet	**0.049**	0.014	**0.021**	0.009
Demographics	*Gender*	**0.139**	0.044	**0.084**	0.027
	Age	−0.002	0.002	−**0.032**	0.010
	Education	0.024	0.015	0.012	0.009
	Income	0.011	0.013	0.008	0.008
	Married	0.094	0.049	**0.059**	0.030
Channel	*Shop*	**0.335**	0.043	**0.229**	0.039
WOM consumption					
	Intercept	−**1.088**	0.157	−**1.271**	0.161
Product experience	*First time*	**0.376**	0.076	**0.314**	0.076
	Mileage	**0.042**	0.010	**0.041**	0.012
	Quantity	0.045	0.033	0.018	0.034
Media exposure	*Print*	−0.003	0.013	0.008	0.016
	Television	0.002	0.016	−0.028	0.016
	Internet	0.017	0.014	**0.056**	0.014
Demographics	*Gender*	−**0.164**	0.045	−**0.136**	0.045
	Age	0.001	0.002	−**0.063**	0.016
	Education	**0.062**	0.015	**0.042**	0.014
	Income	−0.019	0.014	−0.014	0.013
	Married	−**0.173**	0.048	−**0.168**	0.050
Channel	*Shop*	−**0.278**	0.044	−**0.367**	0.057

Note. Bold estimates are the ones that are significant at the 5% level.

or underestimation. This finding helps to establish the validity of the assumption of consumer maximization of the joint utility from WOM generation and WOM consumption and incorporation of the synergy effect.

Robustness Check

Testing the Potential Sample Selection Bias. Note that our proposed model is applied to those who had purchased a car in the last 12 months. This is because the company did not collect WOM information on those who did not purchase a car in the last 12 months. However, there could be sample selection bias if some unobserved personal characteristics led to a correlation between a consumer's car purchase decision in the past 12 months and WOM generation/consumption activities. We performed a sample selection test by adopting the Heckman procedure (Heckman 1978). In this procedure, we modeled the two processes simultaneously as follows: First, we modeled the selection process, i.e., whether a respondent purchased a car in the last 12 months as a function of media exposure and demographics. In our case, we have 4,544 cases of purchase and 19,784 cases of no purchase. Second, we modeled consumer WOM generation/consumption decisions conditional on a car purchase in the last 12 months as a function of product experience, media exposure, demographics, and channel of purchase. Third, we allowed the error term in the selection equation to be correlated with the error term in the generation equation and the error term in the consumption equation. Our results show that the correlation estimate between car purchase and WOM generation is 0.319 (0.402), and the p-value is 0.635. Further, the correlation estimate between car purchase and WOM consumption is 0.479 (1.238), and the p-value is 0.619. The likelihood-ratio tests also confirm the lack of evidence of sample selection bias. In summary, we conclude that the car purchase equation is not significantly correlated with the WOM generation/consumption equation after controlling for observed covariates, and there is no evidence of sample selection bias in our empirical context.

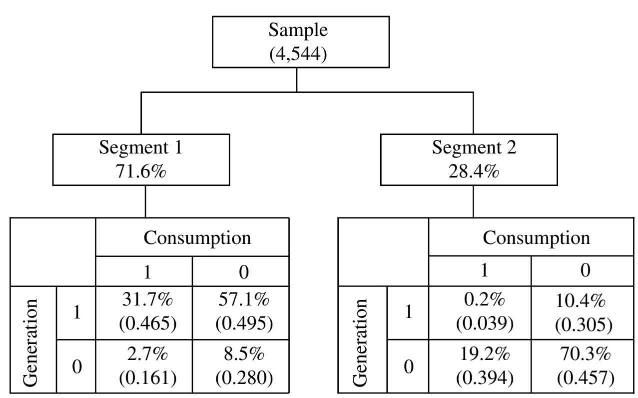
Testing the Potential Endogeneity Bias on Average Media Exposure. In the proposed model, we allow consumer media exposure to predict their WOM activities on cars. However, consumer WOM activities may influence consumer media exposure. For example, people with a high need for WOM consumption watch a lot of TV. This suggests that media exposure could be an endogenous variable. We conducted the endogeneity test on a consumer's average media exposure across the three types of media. Because we do not have panel data, finding appropriate instruments (i.e., variables that are correlated with an individual's media usage but not WOM behaviors) is extremely difficult. We thus followed the literature on accounting for endogeneity without instruments (Dong 2010). Dong adopted a control function approach to test endogeneity. Specifically, the first step involves a nonparametric regression on the suspect endogenous variable, and then residuals from the first step will be used in the second step as a predictor for the dependent variable of interest. In the case of exogeneity, the coefficient of the residual in the second-step estimation will not be significantly different from zero. We applied this method to our context and found that the residual coefficient λ is 0.095 (S.E. $= 0.082$, t-statistic $= 1.15$, p-value > 0.25). This suggests that we cannot reject the null hypothesis of the average media exposure being exogenous. We thus did not find a significant trace of consumer media exposure being endogenously related to consumer WOM activities. This could be partially explained by the design of the questionnaire. The reported WOM activities were specifically related to cars, whereas an individual respondent's media exposure is measured as a total sum independent of any specific product categories.

Managerial Implications

By revising the prior probabilities of membership m_{is} calculated by Equation (7) via updating the priors with observed consumer product experience and media usage information in a Bayesian fashion, we can calculate the posterior probability of each consumer belonging to each segment. Such posterior membership probabilities allow us to assign each consumer to a specific segment (Kamakura and Russell 1989, Gupta and Chintagunta 1994).

The WOM generation and WOM consumption behaviors exhibited in those two segments are drastically different. We report the differences in Figure 2. Note that Segment 1 is three times as large as Segment 2. Consumers in Segment 1 are more likely to generate WOM (88.8% versus 10.6%) and consume WOM (34.4% versus 19.4%). What follows is that

Figure 2 Segment Characterization on WOM Activities



nearly a third of the population in Segment 1 engages in both activities, compared with only 0.2% in Segment 2. Recall that this difference has been captured by the estimate of θ, the synergy effect between the two WOM-related activities in the empirical analysis. θ is positive for Segment 1 and negative for Segment 2. This shows that for consumers in Segment 1, WOM generation and WOM consumption are perceived to be complementary, with one activity encouraging the occurrence of the other. For consumers from Segment 2, these two activities are perceived to be partial competitors as one activity utilizes cognitive resources that actually reduces the other. So in Segment 1, we see a flourish of WOM exchanges, whereas Segment 2 is a rather "quiet" world.

To understand the characteristics of each segment, in Table 9, we compare the two segments on consumer average product experience, media usage, and demographic profiles. In the last column of the table, we report the *p*-value of the test statistics to indicate whether the difference on a particular dimension between the two segments is significant. In summary, we find that consumers in Segment 1 have more product experience. These consumers tend to be younger, be better educated, have a higher income, and have more Internet experience. This segment also includes more males. On the other hand, consumers from Segment 2 are less experienced with the product, are older, are less educated, and have lower income. There are more women than men in this segment, and they tend to watch more TV. We next discuss the managerial implications of these findings on targeting for a firm's effective use of a WOM campaign.

An important finding from our analysis is that there exist two segments of consumers who behave differently in terms of WOM generation, WOM consumption, and the synergy between the two activities. In Segment 1, WOM generation and consumption are active (i.e., higher frequency) and tend to enhance each other (i.e., positive synergy effect), whereas in Segment 2, WOM generation and consumption are inactive (i.e., lower frequency) and tend to hinder each other (i.e., negative synergy effect).

Table 9 Profiles of the Two Segments

Variable	Segment 1	Segment 2	*p*-Value
First time	0.073	0.066	0.377
Mileage	4.036	3.712	0.000
Quantity	1.444	1.382	0.011
Print	3.241	3.257	0.712
Television	3.959	4.145	0.000
Internet	3.260	3.067	0.001
Gender	0.503	0.438	0.000
Age	3.288	3.744	0.000
Education	5.165	4.927	0.000
Income	3.865	3.530	0.000
Married	0.703	0.679	0.116
Shop	0.531	0.528	0.891

Imagine that a company is running a WOM campaign that starts with choosing the "seeds" to trigger a positive WOM. One of the measures of the success of a WOM campaign is *reach*—the number of consumers accessed by the WOM campaign who actually utilize the WOM in their purchase decision. Higher reach can help generate more sales and hence lead to a higher return from a WOM campaign. We conduct the following counterfactual experiment to demonstrate how the proposed model can help understand the impact of seeding strategies on the return of WOM campaigns.

We consider two "seeding" strategies. In the first one, we randomly picked consumers from Segment 1 as the seeds for the WOM campaign. In the second one, we randomly picked consumers from Segment 2 as the seeds for the WOM campaign. We also consider three recipient conditions describing to whom the WOM is passed. In the first one, we assumed that the WOM was passed to a randomly chosen person from our data. Because we do not have friendship data, we used data from our sample as an approximation. In the second one, we assumed the WOM was passed to a consumer with an 80% chance from the same segment as the WOM initiator and a 20% chance from the other segment. In the third one, we assumed that the WOM was passed to a consumer coming from the same segment as the WOM initiator. In the last two scenarios, the implicit assumption is that consumers are more likely to make friends with those who are similar to them.

In each of the six conditions (2 seeding strategies $\times$ 3 recipient conditions), we performed the following simulation. At the initial condition, we randomly picked 10 consumers as the seeds and predicted their WOM generation and consumption behavior. We then calculated the total expected reach at the initial condition by summing up the expected WOM consumption probability over the 10 consumers. We then allowed the consumers who generated WOM in the initial condition to pass it to 10 simulated friends and then calculated the total expected reach after one round of WOM. Similarly, we calculated the total expected reach after two rounds of WOM. We repeated this process 1,000 times to obtain the average expected reach at the initial condition, after one round of WOM, and after two rounds of WOM under each of the six experiment conditions.

Several findings emerge from this counterfactual analysis: (i) Who to select as the seeds of the WOM campaign matters. In our case, we find that seeding with Segment 1 leads to a much higher expected reach than seeding with Segment 2. This is reflected in the larger numbers in Table 10, panel (a), than their

Table 10 Expected Reach of WOM Campaign When Seeding with Segments 1 and 2

Recipient condition	Expected reach (at the initial condition)	Expected reach (after one round of WOM)	Expected reach (after two rounds of WOM)
	(a) Segment 1		
Random	2.7	17.5	113.0
8:2/2:8	2.5	17.7	124.1
Same segment	2.7	22.2	180.9
	(b) Segment 2		
Random	0.9	5.1	33.7
8:2/2:8	1.0	2.9	10.3
Same segment	0.9	1.9	4.8

Note. The seeding strategy was to choose 10 people from each segment.

counterparts in Table 10, panel (b). (ii) The benefit of seeding with Segment 1 relative to seeding with Segment 2 magnifies as the WOM keeps passing further. For example, in the case of random recipient case, the expected reach at the initial condition, after one round of WOM, and after two rounds of WOM is 2.7, 17.5, and 113, respectively, when choosing seeds from Segment 1, in contrast to 0.9, 5.1, and 33.7, respectively, when choosing seeds from Segment 2.

Conclusion

As marketers seek more control over the WOM process, a deep understanding about factors that drive WOM consumption and WOM generation and their synergy effect is crucial for making WOM an effective marketing tool. In this paper, we study these important issues by proposing a model to account for such interdependent effects between the two WOM-related activities and present an empirical application of the proposed model.

We apply the proposed model to survey data collected on the automobile category. Also, we find that consumer product experience and media exposure explain consumer WOM activities. We find that consumer product experience and media exposure are positively correlated with their propensity to generate WOM. However, their effect on WOM consumption is mixed. Consumer product experience and media exposure can positively or negatively explain consumer propensity to consume WOM. Our empirical analysis also provides evidence of unobserved heterogeneity in the way that consumer WOM activities are related to consumer product experience. Finally, consumer demographics play an important role in explaining the difference in WOM consumption and generation behaviors.

We also find that there is a strong synergy between WOM generation and WOM consumption. An interesting finding is that whereas the majority of consumers tend to use WOM generation and WOM consumption in a complementary manner (i.e., participation in one activity encourages participation in the other), some consumers tend to perceive the two activities as competing with each other (i.e., participation in one activity reduces participation in the other). This finding has important managerial implications to auto companies.

Finally, our analysis identifies two segments: one segment having a higher baseline WOM generation and consumption and a positive synergy between the two activities, and the other having a lower baseline WOM generation and consumption and a negative synergy between the two. Based on this finding, a viable targeting strategy would be to seek those active WOM consumers and generators with a positive synergy effect in order to achieve a more effective communication through WOM. As shown in our policy simulation, different seeding strategies (by choosing which segment of consumers as seeds) will lead to different return for a WOM campaign. Seeding consumers with active WOM generation and consumption and a positive synergy between the two generates a higher expected reach for the WOM campaign compared with seeding those with inactive WOM generation and consumption and a negative synergy between the two.

There are several opportunities for extending this work. First, our empirical findings are limited to one product category. It is important to validate these findings using data from other product categories because it would be useful to understand how product characteristics (such as high involvement versus low involvement, experiential product versus search product) explain the differences on the intensity of and the synergy between WOM consumption and WOM generation.

Second, it would be interesting to extend the current analysis to the international context by examining country-specific effects. We collected similar survey data from 200 MBA students at a business school in China. Our findings suggest that there exists a strong synergy effect between WOM generation and WOM consumption, and more importantly, cultural and country-specific factors affect the baseline preference for WOM generation/consumption activities and the synergy effect.

Third, it would also be interesting to explore the effectiveness of different types of WOM at various stages of consumers' purchase and decision-making processes. Finally, because of data limitations, we are not able to explore the WOM volume effect, valence effect, or dynamic effect in this paper. However, these effects can be important, and in such cases, more informative data will be able to address these unexplored issues. We leave these topics to explore in future research.

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