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The Antecedents of Online Word-Of-Mouth

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Abstract

This study makes use of online word of mouth (WOM) data for automobiles to examine the antecedents of online WOM, the multiple factors that either stimulate positive or create negative online WOM, the dynamic pattern of online WOM activities, and the unique, untested influence of TPO endorsements or reviews' on both volume and valence of online WOM. The study contributes to the growing online WOM literature, automobile industry and potentially buzzes marketing management for durable goods, such as computers, digital camera or other consumer electronics.

Introduction

It is a common notion that word-of-mouth (hereafter WOM) plays a major role in influencing consumers' purchase behaviors (Arndt 1967; Brown and Reingen 1987). Of all information channels, researchers suggest that WOM may be the most powerful one (Katz and Lazarsfeld 1955; Day 1971). With the advent of the Internet age, this most ancient mechanism has been given a new significance. A new form of WOM, namely online WOM, allows consumers all over the world to gather unbiased opinions from other experienced consumers or to offer their own consumption advices to others through online WOM platforms (Thurau, Gwinner, Walsh and Gremler 2004). Compared to offline WOM, online WOM may be even more powerful because it extends one-to-one communication to one-to-many and many-to-many communication (Pitt, Berton, Watson and Zinkhan 2002). Although online WOM has played an important role in consumer behavior, only limited studies are related to online WOM to date. The Majority of these studies focus on the effect of online WOM on the sales of culture products, such as movies, books and TV shows (see, e.g. Chevalier and Mayzlin 2006; Liu 2006; Duan, Gu, and Whinston 2005; Dellarocas, Awad, and Zhang 2004; Godes and Mayzlin 2004, Bao and Chang 2014). However, firms are increasingly interested in managing WOM and applying buzz marketing or viral marketing campaign. A better understanding of the drivers of online WOM, such as the factors that produce positive WOM effects and the factors that reduce negative WOM effects, is a prerequisite for the success of such campaigns. A fundamental question has to be answered: what are the antecedents of online WOM? As a matter of fact, very few studies have focused on the antecedents of offline WOM (Anderson 1998; Brown, Barry, Dacin and Gunst 2005), and the findings are generally equivocal (Swan and Oliver 1989; Arnett, German and Hunt 2003). Therefore, it is very necessary even urgent to investigate this issue in detail and develop a relevant theory for it.

Our study differs from many previous online WOM studies because we focus on our attention on one product category –automobile, which has not been investigated in the online WOM literature. We choose automobiles as the product category because: First, it is well known that WOM plays an important role in car purchase behavior (Rosen 2000) and a couple of previous offline WOM researches focus on automobiles as well (e.g. Swan and Oliver).

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Second, the findings of extant online WOM studies may not be able to generalize to durable goods, such as automobiles and computers, because these studies only investigate online WOM for culture goods.

Godes and Mayzlin (2004) suggest that more investigation of online WOM for expensive goods should be developed. Third, automobile buyers are increasingly using online WOM community to gather credible information (Klein and Ford 2001). A number of prestigious sites, such as Yahoo, MSN, Edmunds and Consumer Reports, provide automobile online WOM platforms where online consumer reviewers can post reviews of their cars. Online WOM for automobiles is a major topic that is worthy to draw attentions from both the academic and the industry. The objective of this article is to explore factors relating to online WOM for automobiles. This study attempts to provide answers to the following questions: what drive a car owner to post a car review online? What motivate one consumer to post a positive WOM and another consumer to post a negative WOM? Is online WOM consistent with offline WOM so that a U-shape relationship exists between consumer satisfaction and online WOM activities? Do product characteristics relate to online WOM activities and what are they? Do third-party organization endorsement or reviews have an impact on online WOM?

We collect online WOM data from Consumer Reports website that contains an online consumer reviews platform for automobiles. Our data set consists of 746 car models sold in the United States across six years generations (e.g. 2001 to 2006) and total 16771 online consumer reviews. We fit OLS regressions on the density of online WOM and negative binomial regressions on the volume of online WOM in three levels: the disaggregated level, the aggregated level and the generation level. 22 regressions analysis yield consistent results: online WOM for automobiles are related to consumer satisfaction level, some product characteristics and third-party endorsements or reviews. Specifically, we find some evidence to support a U-shape relationship between consumer satisfaction and online WOM; some product characteristics, such as newness, fanciness, expensiveness and uniqueness, stimulate online WOM; third-party organization endorsements or reviews have a great influence on both volume and valence of online WOM. Our study contributes to the online WOM literature and automobile industry. By addressing the issue for the online context, this study also provides some insights for the WOM in general. Last, but not least, our study provides implications of buzz management, especially for durable goods.

Literature Review and Theoretical Background

To our knowledge, there are only three marketing studies to date that are related to the antecedents of online WOM. Liu (2006) regresses the volume of online WOM for movies on movie genres, MPAA ratings, star powers, the number of critical review and the volume of WOM in the previous week. He finds that most of explanatory powers are from the volume of WOM in the previous week. Surprisingly, star powers and critical reviews have no significant impact on the volume of WOM. Dellarocas and Narayan (2006) also investigate antecedents of online WOM for movie. Unlike using the volume of WOM as the dependent variable, they propose a new metric of WOM, namely density, which is defined as the estimate of conditional probability that a consumer who has purchased a product will give an online review. They find that a U-shape relationship between perceived movie quality and density of reviews. They also find that marketing expenditures and product exclusivity are positively correlated to higher propensity to engage in online WOM. In addition, movie genres are related to online WOM. Thurau, Gwinner, Walsh and Gremler (2004) investigate why consumers would like to engage in online WOM activity in general. Their findings identify four factors leading to online WOM behavior, namely consumers' desire for social interaction, desire for economic incentives, concern for others and improvement of self-worth.

Previous online WOM studies tell us a lot about online WOM behavior for cultural goods. Their works suggest that consumer satisfaction (e.g. perceived quality in Dellarocas and Narayan 2006), product characteristics (e.g. MPAA ratings and star powers in Liu 2006; movie genres and the number of screens in Dellarocas and Narayan 2006), and third-party reviews (e.g critical reviews in Liu 2006) are potentially related to online WOM. In line with this stream of studies, we suggest that consumer satisfaction toward a car, some product characteristics of a car and third-party organization endorsements or reviews about a car should be included together as a complete theoretical framework in a model to examine the relationships between them and online WOM for automobiles. Previous offline WOM studies have considered customer satisfaction as a major antecedent of WOM. Swan and Oliver (1989) investigate the three types of post purchase communications about automobile: positive/negative WOM, recommendations/warnings to other people and complaints/compliments. They find that as customer satisfaction increases WOM become more positive, and a car, car dealer and salesman are more likely to be recommended. Richins (1983) examines the relationship between dissatisfaction and negative WOM.

She finds that as the level of dissatisfaction increases customers are more likely to spread negative WOM. However, minor dissatisfaction is unlikely to stimulate negative WOM. Anderson (1998) suggests a U-shape instead of traditional linear relationship between customer satisfaction and WOM.

In this framework, WOM activity increases as satisfaction increases or dissatisfaction increases. Thus:

H_1: There exists a U-shape relationship between consumer satisfaction toward a car and online WOM activities about the car, such that more satisfied with a car more positive online WOM activities generate and more dissatisfied with a car more negative online WOM activities generate.

It is almost a common sense that some product characteristics are related to WOM behavior. After all, WOM is about products. WOM is especially crucial for the adoption of new products since awareness must be built (Mahajan, Muller and Kerin 1984). In his book about WOM, Rosen (2000) point out that people generally like to talk about innovative products. Several behavioral researches suggest that self-enhancement is a great motive for WOM behavior (Engel, Blackwell and Miniard 1993; Sundaram, Mitra and Webster 1998). Talking about new products of which people generally have limited knowledge certainly allows a person gain a great attention and makes him/her an intelligent shopper. In addition to newness, some other characteristics, such as expensiveness, fanciness and uniqueness of a product are more likely to make the owner of a product feel excited about it. Derbaix and Vanhamme (2003) find that a emotional reponse, such as surprise, can sitimulate both positive and negative WOM activities. Rozen's book provides a great example of this, with its stunning design, BMW Z3 created a good buzz and a big sale. Thus:

H_2: Some product characteristics are related to online WOM. The newness of a car is positively related to online WOM. An expensive, fancy or unique car can stimulate more online WOM activities than an inexpensive, ordinary or common car.

Third-party organization (hereafter TPO) endorsements (Feng, Wang and Peracchio 2008) or critical reviews have grown increasingly popular in recent years particularly because a new generation of independent information sources emerges online. Numerous TPO websites, which cover a variety of product domains, e.g. automobile, computer, movie, sports shoes, and so on, are regularly offering many forms of product endorsement and reviews. A stream of research began to focus on TPO endorsement and critical reviews (e.g.Chen and Xie 2005; Eliashberg and Shugan 1997; Basuroy, Chatterjee and Ravid, 2003). Eliashberg and Shugan (1997) investigate the role of a critic in movie industry. They favor the role as a predictor other than an influencer. Basuroy, Chatterjee and Ravid (2003) argue that movie critics play a dual role: critics can influence and predict a movie's success. In both Eliashberg and Shugan's study and Basuroy et al.' s study, WOM is considered as a substituting power of critical reviews after films are open to the public. Whether or not WOM is influenced by critical reviews is not investigated and discussed. The only exception is Liu's study about WOM's effect on box office revenue. Liu (2006) considers critical reviews as a potential antecedent of WOM because critical reviews may influence moviegoers' expectation of a film and thus correlate with WOM.

However, the empirical analysis shows that there is no relationship between the volume of critical reviews and the volume of online WOM. Possible reasons for this result are: 1) consumer reviewers who provide online WOM may not be able to read the critical reviews that are analyzed in this study; 2) the volume of critical reviews alone is not enough to capture an effect on WOM. The influence of positive critical review or negative critical review on WOM should be further investigated. Although there is no published evidence that there is a relationship between TPO endorsement or critical reviews and WOM activity, there are some reasons to believe this relationship exists. First, TPO endorsements or reviews provide more knowledge of reviewed products to consumers, stimulating consumers to be more involved with the products and have more interests in talking about the reviewed products or services. Second, TPO endorsement or reviews may generate placebo effect on consumer perceived quality (Shiv, Carmon and Ariely 2005), and thus influence both the volume and direction of WOM. Third, TPO endorsements or reviews narrow people's attention to good brands or bad brands, leading consumers with opinion leadership characters to stand out (e.g. supporting TPO reviews or challenging TPO reviews). Finally, TPO endorsements or reviews may strengthen satisfied customers' confidence in talking about their own consumption experiences. Thus:

H_3: TPO endorsements or reviews are related to online WOM for automobiles. Positive TPO endorsements or reviews for a car stimulate positive online WOM activities, whereas negative TPO endorsements or reviews for a car create more negative online WOM activities.

Data

We collect online WOM data[3] from the Consumer Opinion platform at Consumer Reports (Hereafter CR) website. There are actually many websites providing platforms where online users can rate and post comments on various car models. Table 1 classifies five major websites that provide online WOM platforms into four categories. We choose CR data for several reasons: first, consumers need to pay a member fee (e.g. $25 per year) to view other consumers' reviews or post their own reviews at CR website, which increases the credibility of our online WOM data[4]; second, CR website has a great influence on car buyers. The findings from Ratchford, lee and Talukdar (2003) show that 12.68% of online automobile information searchers use Edmunds, 6.59% of them use Consumer Reports, and 4.15% of them use Yahoo car guides; third, unlike specialized consumer review websites, which are developing in just recent years (e.g. Epinion.com), CR website is a third-party organization (TPO) website, which also provides scientific lab or survey reports, third-party organization awards and reviews. Therefore, by analyzing CR data, we may be able to examine a unique relationship between CR's brand/model endorsement action and online WOM activities occurring at CR website.

Table 1: Summaries of Five Websites that Provide Online Consumer Reviews Platforms

	TPO or specialized consumer review website	Free Post/Visit	Specialized in automobile	Influence
Edmunds	TPO	Yes	Yes	12.68%
Epinion	Specialized consumer review	Yes	No	N/A
Yahoo	TPO	Yes	Yes	4.15%
Consumerreports	TPO	No	Yes	6.59%
Consumerreview	Specialized consumer review	Yes	No	N/A

At CR website, the procedure of posting a consumer review is the following steps: first of all, a visitor needs to register as a member of CR website and pay a member fee; Second, this member can choose the car model he/she is going to review (e.g. choosing maker, year, model, trim line); Third, he/she rates the model using 5 star points (e.g. 5='love it', 4='pretty good', 3='Ok', 2='not so hot' and 1='hate it'); Fourth, he/she inputs main ideas (e.g. title, pros, cons); Finally, he/she inputs detailed comments (e.g. driving experience, comfort and overall comments). As we described above, a consumer reviewer needs to go through a very complex procedure to offer a car review without any compensation. However, over 20,000 consumer reviewers have provided their reviews at CR website. What are drivers of this online WOM behavior? CR website began to run this online consumer review platform around February 2004. All car models sold in U.S. ranging from 2000 car models to 2008 car models are listed for being reviewed. We complete collecting consumer reviews data for six generations of car models[5] within one week[6] in June 2007. In addition to collecting the number of total online consumer reviews (TWOM) for each car model, we also collect the number of positive online consumer reviews (PWOM), the number of negative online consumer reviews (NWOM) and the number of mixed online consumer reviews (MWOM) for each car model[7]. Table 2 and figure 1 shows that reviews are overwhelmingly positive, which is consistent with the findings of Chevalier and Mayzlin (2006). A time-series plot (see figure 2) shows that the average number of online consumer review is generally increasing from 2001 model to 2006 model, while figure 3 shows that average sales of a car model is generally decreasing from 2001 model to 2006 model.

[3] We also collect the volume of total online consumer reviews for 2005 car models from Edmunds.com.
[4] Mayzlin (2006) discusses firms can anonymously post online consumer reviews.
[5] Six generations of car models are: 2001 car models, 2002 car models, 2003 car models, 2004 car models, 2005 car models and 2006 car models.
[6] We collect online consumer reviews data in a short period time because the number of online consumer reviews for each car model increases at a daily basis. We minimize this potential issue by collecting all data in a week.
[7] We define a consumer review with 5 stars as a positive review because 5 stars means reviewers 'love the model'.We define a consumer review with 1 star or 2 stars as a negative review because this review means that reviewers either 'hate the car model' or feel it 'not so hot'. We further define a consumer review with 4 stars or 3 stars as a mixed review because the scales are between extreme positive and extreme negative scales.

Obviously, people's common wisdom, "more sells, more word-of-mouth", cannot explain this finding. Following the theoretical framework we propose in the previous section, we collect data, which capture three aspects: consumer satisfaction level toward a car model, some product characteristics of a car model and TPO endorsements or reviews about a car model.

Table 2: Summaries of online Consumer Reviews

	Number of online consumer reviews for the year car models	Number of online consumer reviews rating the year car models as 5 (love it)	Number of online consumer reviews rating the year car models as 4.	Number of online consumer reviews rating the year car models as 3.	Number of online consumer reviews rating the year car models as 2.	Number of online consumer reviews rating the year car models as 1 (hate it).	Average number of consumer reviews for each car model	Number of car models sold in US market in that year	Model name of receiving highest consumer reviews (number of reviews)
2006 Model	4801	3388	884	223	208	98	16.67	288	Honda Civic (136)
2005 Model	5565	3813	1158	272	210	113	21.16	263	Toyota Prius (219)
2004 Model	3481	2068	934	221	168	90	14.21	245	Toyota Sienna (148)
2003 Model	3079	1675	960	210	162	72	13.45	229	Honda Accord (148)
2002 Model	2642	1293	874	211	182	82	12.06	219	Toyota Camry (104)
2001 Model	2297	1055	764	234	159	85	10.990	209	Honda Odyssey(76)
Total	21865	13292	5574	1371	1089	540	15.048	1453	Toyota Prius (219)

Figure 1: Number of Online Consumer Reviews Given Different Ratings

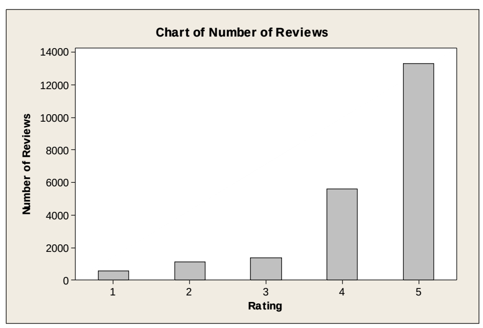


Figure 2: Average Numbers of Online Consumer Reviews for the Car Model Vary in Different Generations

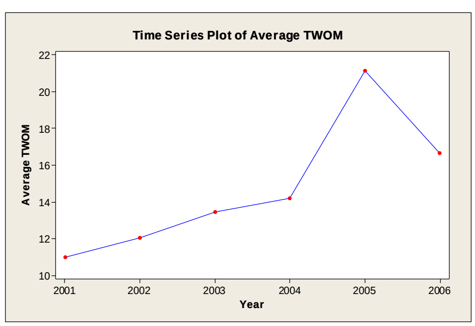
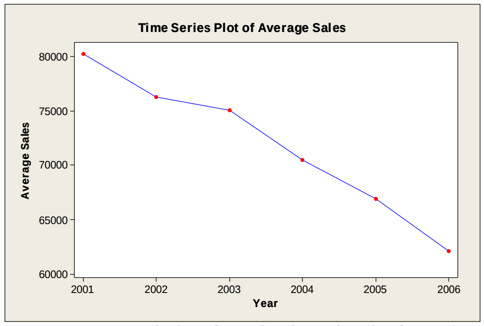


Figure 3: Average Sales for the Car Model Vary in Different Generations



*Consumer satisfaction*We collect customer satisfaction index (CS) data from CR website. CR website states that "Car Owner Satisfaction Survey drew responses about more than 415,000 individual vehicles and more than 300 models".

Owner-satisfaction ratings are determined by the percentage of those who answered "definitely yes" to the following survey question: "Considering all factors (price, performance, reliability, comfort, enjoyment, etc.), would you get this car if you had to do it all over again?" Therefore, consumer satisfaction index from CR could be regarded as a population estimated consumer satisfaction level toward a specific a car.

Product characteristics We collect three characteristics of a car model from CR: the history of a car model(HIS), whether a specific year model is a new or re-designed model (NEW) and the vehicle type of a car model. The history of a car model reflects how many years has this car model been in U.S. car market?Some models have a very long history. Infiniti G, for example, has 15 year of history as 2005 infiniti G was introduced into the market. Honda Pilot was introduced in 2003, and therefore it has 4 years history when 2006 Honda Pilot entered the market. Moreover, many automobile makers regularly redesign or introduce a totally new model in a specific year, which means this model is relatively new compared to other models in a specific year. Toyota, for example, introduced Tacoma in 1995, and Toyota redesigned Tacoma in 2005. Therefore, we treat 2005 Toyota Tacoma as a new or redesigned model. Finally, we classify each car model into one of 10 vehicle types, SUV, pickup, van, sports, luxury, small, large, family, coup and wagon.

TPO endorsements or reviews We use Consumer Reports' Good Bets and Bad Bets as TPO endorsements or reviews. We assume that an online consumer reviewer has exposed to this information source before they post a review. This is a valid assumption because: 1) every reviewer pays a fee to receive information from CR website and CR is famous for its automobile quality report; 2) CR website offers endorsements or reviews for each generation car model before online consumer reviewers start to post reviews. We define CR's Good Bets as positive TPO endorsements or reviews (CRGOOD) and CR's Bad Bets as a negative TPO reviews (CRBAD).

Table 3 shows two car models given the data we have collected. For instance, there are 316638 2006 Honda Civic sold. 136 owners of 2006 Honda Civic went to CR websites to offer reviews, and 83 out of them gave positive reviews, 12 out of them gave negative reviews and 41 out of them gave mixed reviews. According to CR's consumer satisfaction index, 81% owners of Honda Civic satisfy with Civic. When 2006 Civic was introduced to the market, Honda Civic has been in the market for 11 years. Honda company re-designed 2006 Civic and CR awards Honda Civic "Good Bets".

Table 3: Two Car Models Given Collecting Data

Brand & Model	Year of the Model	Unit Sales (SALES)	Number of Reviews Posted (TWOM)	Number of Positive Reviews Posed (PWOM)	Number of Negative Review Posted (NWOM)	Number of Mixed Review Posted (MWOM)	Consumer Satisfaction Index (CS)	History of the Model (HIS)	New or Re-designed in that year (NEW)	Endorsed by Consumer Reports as Good Bets (CRGOOD)	Reviewed by Consumer Reports as Bad Bets (CRBAD)	Vehicle Type
Honda Civic	2006	316638	136	86	12	41	81%	11	Yes	Yes	No	Small
Audi A4	2003	51043	11	6	4	1	67%	8	No	No	No	Upscale

Empirical Analysis and Discussion of Results

Total Online Consumer Reviews for a Car

One of advantages of emerging Online WOM phenomena is that for the first time, researchers are able to observe and record real WOM behavior through the online community.

Four measurements of online WOM have been suggested in the previous literature: volume or number (Liu 2006) is defined as how many online consumer reviews toward a specific product or service; dispersion (Godes and Mayzlin 2004) is referred to how WOM spread among different groups; valence (Dellarocas, Awad, and Zhang 2005) look at the attitude of each message (e.g. positive or negative WOM); and density is proposed by Dellarocas and Narayan (2006) and is defined as the propensity to engage in online WOM. Since we are interested in an online consumer reviewer's propensity to offer a car review given that he/she owns the car model. The density of online consumer reviews fits our interests well.

We could see the density of online consumers reviews as a conditional probability:

$$\begin{aligned} Density &= P({}^{reviewer\ j\ reviews\ i}\!/_{reviewer\ j\ owns\ i}) \\ &= \frac{P({}^{reviewer\ j\ owns\ i}\!/_{reviewer\ j\ reviews\ i}) \times P(reviewer\ j\ reviews\ i)}{P(reviewer\ j\ owns\ i)} \\ &= \frac{P(reviewer\ j\ reviews\ i)}{P(reviewer\ j\ owns\ i)} \\ &= \frac{number\ of\ total\ online\ consumer\ reviews\ for\ i}{unit\ sales\ for\ i} \end{aligned} \tag{1}$$

Where we assume that $p({}^{reviewer\ j\ owns\ i}\!/_{reviewer\ j\ reviews\ i}) = 1$, and that means reviewers only review the cars they own. Since we have data for the number of total online consumers reviews (TWOM) and unit sales (SALES), we are able to calculate density of total online consumer reviews (DENTWOM) for each car model.

$$DENTWOM_i = \frac{TWOM_i}{SALES_i} \tag{2}$$

We then apply a logit transformation to linearize its relationship with a set of independent variables (Greene, 2003). Specially, the following model is estimated:

$$\begin{aligned} Log\left(\frac{DENTWOM_i}{1-DENTWOM_i}\right) &= \beta_0 + \beta_1 CS_i + \beta_2 CS_i^{\,2} + \beta_3 HIS_i + \beta_4 NEW_i + \sum_{i=5}^{13} \beta_i VehicleType \\ &+ \beta_{14} CRGOOD_i + \beta_{15} CRBAD_i + \sum_{i=16}^{20} \beta_i YEARMODEL + \varepsilon_i \end{aligned} \tag{3}$$

To capture a U-shape relationship between consumer satisfaction and online WOM, we include both first- and second-degree term of CS. Furthermore, we used mean-centered CS to avoid multicollinearity problems between CS and CS^2. VehicleType and YearModel are dummy variables and we set SUV and 2001MODEL as the baselines. Table 4 lists all variables and their meanings, and table 5 provides the mean, and standard deviation of the variables. A correlation matrix among continuous independent variables is illustrated in table 6.

Table 5: Key Summary Statistics of Variables Used in the Analysis

Variable	Mean	SD
SALES	78440.26	78955.17
TWOM	22.48	24.9
PWOM	14.02	17.66
NWOM	1.57	2.25
MWOM	6.89	8.02
CS	66.95%	11.65%
HIS	7.39	4.29

Table 6: Correlation Matrix among Continuous Independent Variables

Variables	CS	CS^2	HIS
CS	1.000	--	--
CS^2	-0.24 (0.000)	1.000	--
HIS	0.063 (0.08)	0.155 (0.000)	1.000

We fit this OLS regression model in both the disaggregated level and aggregated level. In the disaggregated level, an individual observation is a car model in a specific generation (e.g. 2005 Honda Civic); while in the aggregated level, an individual observation is a car model (e.g. Honda Civic). In other words, in the aggregated level, the number of total online consumer reviews for a car is the sum of the number of total online consumer reviews of each generation model. A density distribution of residuals (Figure 4) for the model in the disaggregated level shows that residuals follow a perfect normal distribution. Moreover, a plot of residuals versus fitted values (Figure 5) does not present heteroskedastic errors[8]. We also examine the relationship between the model covariates for damaging multicollinearity. All variance inflation factors VIF are less than 2.5, which indicates that multicollinearity is not a concern.

Figure 4: A Density Distribution of Residuals for the OLS Model on the Number of Online Consumer Reviews in a Disaggregated Level

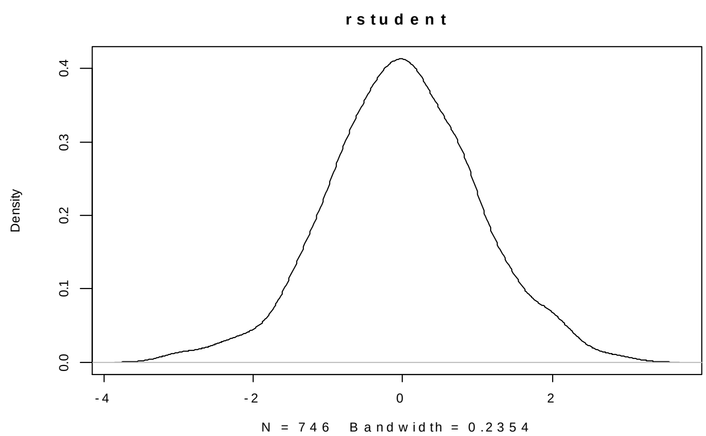


Figure 5: Residuals vs. Fitted Plot for the OLS Model on the Number of Online Consumer Reviews in a Disaggregated Level

[8] We check normality and equal variance assumptions for each OLS regression model estimated in our study. No serious issues rise and therefore we do not report this for each OLS regression model.

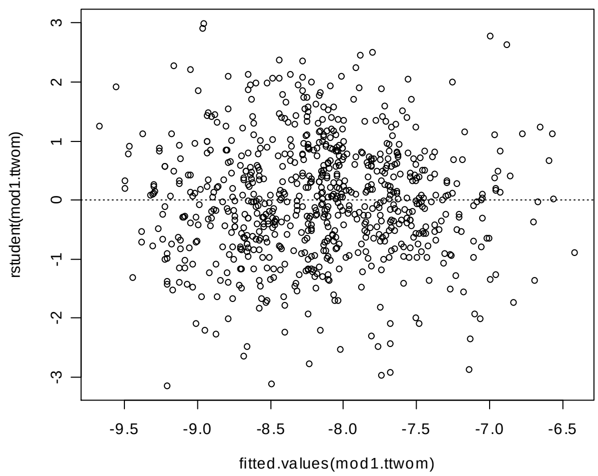


Table 7 presents OLS regression results for total online consumer reviews in both the disaggregated level and aggregated level. Our theoretical framework suggests that online WOM at CR are related to consumer satisfaction, some product characteristics and CR's endorsement actions. Specially, first of all, we expect that there exists a U-shape relationship between consumer satisfaction level toward a car model and the propensity to offer an online consumer review for this car model.

In the disaggregated level, the CS is significant and positive and CS^2 is significant at 7% level and positive, which marginally supports this hypothesis[9]. This finding is consistent with classical CS-WOM relationship in the offline context, and it basically suggests that online consumer reviewers are more likely to offer reviews either when they highly satisfied with their cars or when they highly dissatisfied with their own cars. More specifically, we expect that when more online reviewers satisfied with their car models they contribute more positive reviews and when more online reviewers dissatisfied with their car model they contribute more negative reviews. This hypothesis will be examined in the following analysis on the valence of online WOM.

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[9] However, this is not the case in an aggregated level where CS is positive and significant, but second-degree term of CS is not significant. A possible reason for this inconsistency is that the sample size in an aggregated level is not large enough. In an aggregated level, we have 176 observations while in a disaggregated level we have 746 observations.

Table 7: OLS Regression on Number of Total Online Consumer Reviews in a Disaggregated and Aggregated Level

	Number of total online consumer reviews for a car model in an disaggregated level			Number of total online consumer reviews for a car model in an aggregated level
	1	2	3 (full)	4 (full)
Intercept	-8.585(-94.353)***	-8.576(-90.061)***	-8.714 (-90.501)***	-.01179(-5.377)***
CS	0.033(12.756)***	0.030(11.803)***	0.020 (6.742)***	2.306e-02(4.148)***
CS^2	0.0002(1.094)	0.0005(2.471)**	0.0003 (1.804)*	3.414e-04 (0.998)
HIS (YEAR)	--	-0.041(-5.887)***	-0.043 (-6.383)***	5.478e-02(4.996)***
NEW	--	0.392(5.853)***	0.403 (6.179)***	2.021e-01 (1.592)
PICKUP	--	-0.267(-1.866)*	-0.203 (-1.443)	-3.599e-01 (-1.278)
VAN	--	0.139(1.102)	0.091 (0.728)	-8.008e-02 (-0.333)
SPORTS	--	0.157(1.339)	0.339 (2.870)***	2.630e-01 (1.213)
LUXURY	--	0.502(6.749)***	0.572 (7.812)***	3.083e-01 (2.203)**
SMALL	--	-0.248(-2.046)**	-0.308 (-2.608)***	-.6379(-2.844)***
LARGE	--	-0.196(-1.244)	-0.119(-0.770)	-2.229e-01 (-0.843)
FAMILY	--	-0.003(-0.031)	-0.005(-0.050)	-1.973e-01 (-1.090)
COUP	--	0.008(-0.029)	0.102 (0.392)	-1.390e-01 (-0.295)
WAGON	--	0.144(0.976)	0.136 (0.941)	-1.270e-01 (-0.507)
CRGOOD	--	--	0.465(6.487)***	4.674e-01(3.292)***
CRBAD	--	--	0.038 (0.427)	9.764e-02 (0.586)
2006MODEL	0.691(6.436)***	0.831(8.190)***	0.850(8.606)***	--
2005MODEL	0.703(6.455)***	0.788(7.727)***	0.800(8.052)***	--
2004MODEL	0.330(2.961)***	0.383(3.704)***	0.387(3.849)***	--
2003MODEL	0.141(1.223)	0.171 (1.609)	0.170 (1.643)	--
2002MODEL	0.108(0.904)	0.139(1.268)	0.128 (1.204)	--
R^2	0.2452	0.3808	0.415	0.3907
N=	746	746	746	176

Notes: 1. *** P<0.01; **P<0.05; *P<0.1
2. t-statistics are shown in parentheses.
3. The dependent variable is a logit transformation of the density of consumer reviews for a car model
4. In an aggregated level, we use the year (YEAR) when a car model was introduced into the U.S. market as a proxy of the car model's history.

Second, we expect that some product characteristics, such as newness, fanciness, expensiveness and uniqueness of a car stimulate online WOM activities toward the car.

The HIS is negative and significant in the disaggregated level, and its counterpart YEAR in the aggregated level is positive and significant. This is as expected. Recall that in the aggregated level, YEAR is the exact year when a car model was introduced into the market. Therefore, the smaller YEAR indicates an old car model and the larger YEAR indicated a relatively new car model. The finding indicates that a negative relationship between the history of a car model and the propensity to offer a consumer review for this car model. The NEW is positive and significant in the disaggregated level. However, the same coefficient is positive and insignificant in the aggregated level. Recall that the term of NEW in the aggregated level is coded by counting the events of redesigning a car model or introducing a totally new model within the period (e.g. from 2001 to 2006) recorded in our data, whereas the NEW in the disaggregated level is a dummy variable, and therefore it captures more information than its counterpart in the aggregated level does. This finding suggests that online consumer reviewers generally are more likely to offer reviews for a totally new or re-designed car model versus a "not new" model. Regarding the fixed effects of vehicle type, table 7 shows that in both the disaggregated and aggregated level, the LUXURY has a significant positive effect in car owners' propensity to review a car model, whereas the SMALL has a significant negative effect. Recall that the baseline vehicle type is SUV, and this type is the middle type between SMALL and LUXURY in terms of expensiveness, fanciness and uniqueness.

Therefore, the findings imply that online consumer reviewers generally prefer to offer reviews about expensive, fancy and unique car models over inexpensive and ordinary car models.

Third, we reason that CR's endorsement actions influence on online WOM at CR. Table 7 shows that CRGOOD is positive and significant in both the disaggregated and aggregated level, whereas CRBAD is positive and insignificant[10]. This finding suggests that online consumer reviewers at CR website are more likely to offer a review if their car models are endorsed by CR. We further hypothesize that an online consumer reviewer at CR website is more likely to offer a positive review if his/her car model is endorsed by CR, whereas he/she is more likely to offer a negative review if his/her car model is criticized by CR. The following section of analysis is going to examine this hypothesis.

Positive, Negative and Mixed Online Consumer Reviews for a Car

Total online consumer reviews for a car may only tell us the part of a story. Two cars can have the same number of total online consumer reviews because of different reasons. Considering the following example from our data: both 2005 Pontiac Montana SV6 and 2005 Kia Spectra receive 8 reviews, but Pontiac had 3 positive reviews and 5 negative reviews whereas Kia had 7 positive reviews and only 1 negative review. Examining the valence of online WOM enables us to describe a more complete picture of online WOM activities. Moreover, from the perspectives of managers, they are more interested in finding the factors that stimulate positive online WOM or create negative online WOM, so that managers may be able to control these factors to maximize positive WOM effects or minimize negative WOM effects.

Following the method we apply in previous analysis, we first calculate the density of positive online consumer reviews (DENPWOM), density of negative online consumer reviews (DENNWOM) and density of mixed online consumer reviews (DENMWOM):

$$DENPWOM_i = \frac{PWOM_i}{SALES_i} \quad (4)$$

$$DENNWOM_i = \frac{NWOM_i}{SALES_i} \quad (5)$$

$$DENMWOM = \frac{MWOM_i}{SALES_i} \quad (6)$$

Then, we applied a logit transformation to three dependent variables. Specially, the following models are estimated:

$$Log(\frac{DENPWOM_i}{1-DENPWOM_i}) = \beta_0 + \beta_1 CS_i + \beta_2 HIS_i + \beta_3 NEW_i + \sum_{i=4}^{12} \beta_i VehicleType \quad (7)$$

$$+ \beta_{13} CRGOOD_i + \beta_{14} CRBAD_i + \sum_{i=15}^{19} \beta_i YEARMODEL + \varepsilon_i$$

$$Log(\frac{DENNWOM_i}{1-DENNWOM_i}) = \beta_0 + \beta_1 CS_i + \beta_2 HIS_i + \beta_3 NEW_i + \sum_{i=4}^{12} \beta_i VehicleType \quad (8)$$

$$+ \beta_{13} CRGOOD_i + \beta_{14} CRBAD_i + \sum_{i=15}^{19} \beta_i YEARMODEL + \varepsilon_i$$

$$Log(\frac{DENMWOM_i}{1-DENMWOM_i}) = \beta_0 + \beta_1 CS_i + \beta_2 HIS_i + \beta_3 NEW_i + \sum_{i=4}^{12} \beta_i VehicleType \quad (9)$$

$$+ \beta_{13} CRGOOD_i + \beta_{14} CRBAD_i + \sum_{i=15}^{19} \beta_i YEARMODEL + \varepsilon_i$$

We fit OLS regression models for positive, mixed and negative online consumer reviews in both the disaggregated and aggregated level.

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[10] Recall the findings from figure 1, we observe a large amount of 5-stars consumer reviews and a small amount of 1 or 2 –stars reviews, and hence online consumer reviews are overwhelmingly positive. Hence, we may be able to observe a great impact of CRGOOD on positive reviews while a small impact of CRBAD on negative reviews because of the nature of online consumer reviews data.

Table 8 summarizes the results of our regression analysis. In terms of positive online consumer reviews, the CS is significant and positive in both the disaggregated and aggregated level. In terms of negative online consumer reviews, the CS is negative and significant at 9% in the aggregated level but insignificant in the disaggregated level. Regarding to mixed reviews, the CS is insignificant in both levels. These findings suggest that the more satisfied car owners toward a car model, the more positive online consumer reviews generate. However, we only have partial evidence to support the idea that more dissatisfied car owners toward a car model are, more negative online consumer reviews generate. Moreover, the consumer satisfaction level has no explanatory power to explain mixed online consumer reviews. This is not surprise because an online consumer reviewer who rates his/her car model as 4 or 3 – stars and offers a mixed review is possibly not motivated by his/her satisfaction level but some other factors.

Table 8: OLS Regression on Positive/Mixed/Negative Online Consumer Reviews in a Disaggregated and Aggregated Level

	Number of consumer reviews for a car model in a disaggregated level			Number of consumer reviews for a car model in an aggregated level		
	Positive WOM	Mixed WOM	Negative WOM	Positive WOM	Mixed WOM	Negative WOM
Intercept	-11.573(-49.842)***	-9.719(-40.844)***	-1.043e+01 (-31.506)***	-1.535e+02 (-6.580)***	-80.361(-3.442)***	-62.360 (-1.919)*
CS	0.0311(9.513)***	0.002(0.633)	-4.368e-04 (-0.090)	3.740e-02 (6.373)***	0.001 (0.240)	-0.013(-1.687)*
HIS (YEAR)	-0.045(-5.991)***	-0.034(-4.303)***	-2.122e-02 (-1.998)**	7.110e-02(6.110)***	0.035(3.040)***	0.026 (1.614)
NEW	0.344(4.780)***	0.373(4.986)***	2.638e-01 (2.752)***	2.339e-01 (1.737)*	0.124(0.920)	0.090(0.494)
PICKUP	-0.301(-1.903)	-0.014(-0.092)	-5.345e-01 (-2.409)**	-4.324e-01 (-1.508)	-0.144 (-0.505)	-0.777 (-2.121)**
VAN	-0.013(-0.099)	0.182(1.329)	8.419e-02 (0.511)	-1.413e-01(-0.596)	0.102(0.429)	0.322 (1.023)
SPORTS	0.443(3.373)***	0.259(1.800)*	6.165e-01(2.978)***	3.199e-01(1.391)	0.189 (0.825)	0.356(1.174)
LUXURY	0.684(8.428)***	0.431(4.896)***	8.252e-01(6.827)***	4.110e-01(2.770)***	0.036(0.242)	0.606 (3.054)***
SMALL	-0.364(-2.759)***	-0.256(-1.951)*	-4.561e-01(-2.786)***	-6.412e-01(-2.700)**	-0.540 (-2.280)**	-0.436 (-1.438)
LARGE	-0.021(-0.121)	-0.161(-0.885)	-2.043e-01(-0.792)	-1.205e-01 (-0.430)	-0.443 (-1.581)	0.027 (0.066)
FAMILY	0.032(0.314)	-0.030(-0.290)	-1.941e-01(-1.352)	-1.585e-01 (-0.826)	-0.112 (-0.583)	-0.408 (-1.579)
COUP	0.328(1.154)	0.310(0.770)	4.367e-01(0.844)	8.832e-02 (0.177)	-0.792 (-1.587)	-0.163 (-0.255)
WAGON	0.143(0.909)	0.122(0.742)	3.163e-03(0.015)	-1.294e-01 (-0.487)	-0.137 (-0.517)	-0.451 (-1.257)
CRGOOD	0.576(7.295)***	0.523(6.236)***	-2.403e-01(-1.954)*	5.210e-01 (3.462)***	0.547 (3.634)***	0.053 (0.264)
CREAD	-0.065(-0.660)	0.034(0.315)	5.042e-01(4.017)***	2.444e-02 (0.138)	-0.009(-0.053)	0.789 (3.459)***
2006MODEL	1.259(11.321)***	0.215(1.875)*	1.745e-01(1.127)	--	--	--
2005MODEL	1.217(10.914)***	0.247(2.160) **	1.321e-01(0.833)	--	--	--
2004MODEL	0.620(5.483)***	0.090(0.769)	5.698e-02(0.360)	--	--	--
2003MODEL	0.296(2.543)**	0.033(0.278)	-1.866e-01(-1.154)	--	--	--
2002MODEL	0.206(1.712)*	0.123(0.999)	-2.477e-02(-0.144)	--	--	--
R^2	0.5209	0.1911	0.2784	0.5262	0.1829	0.2739
N=	721	669	450	176	175	159

Notes: 1. *** P<0.01; **P<0.05; *P<0.1
2. t-statistics are shown in parentheses.
3. For Positive WOM, the dependent variable is a logit transformation of the density of positive consumer reviews for a car model; for Negative WOM, the dependent variable is a logit transformation of the density of negative reviews; for Mixed WOM, the dependent variable is a logit transformation of the density of mixed reviews.

The HIS is negative and significant across positive, mixed and negative online consumer review in the disaggregated level, and its counterpart YEAR in the aggregated level is positive and significant. These findings suggest that the shorter the history of a car model is, the high likelihood being reviewed online and this is the case across positive, mixed and negative online consumer reviews. The NEW is significant and positive across positive, mixed and negative online consumer reviews in the disaggregated level. This suggests that online consumer reviewers are generally more likely to offer positive, mixed or negative reviews if their car models are totally new or re-designed models. Combining with findings from the aggregated level where the NEW is positive and significant only for the number of positive online consumer reviews, we may suggest that online consumer reviewers may particularly like to offer positive reviews. Recall our first analysis without the valence of online WOM, where the HIS has a negative sign and the NEW has a positive sign, we can conclude that online consumer reviewers generally like to review a "new" car model and the newness of a car is a strong positive driver of online WOM behavior. In terms of vehicle types, the LUXURY is positive and significant and the SMALL is negative and significant across positive, mixed and negative online consumer reviews in the disaggregated level. This is also generally the case in the aggregated level.

In terms of CR's endorsement actions on positive, mixed and negative online consumer reviews, we have some interesting findings. First, for the positive online consumer reviews, the CRGOOD is positive and significant in both the disaggregated level and aggregated level. This indicates that an online consumer reviewer at CR website is more likely to offer a positive review if his/her car model is endorsed by CR; second, for the negative online consumer reviews, the CRBAD is positive and significant in both levels. That suggests that online consumer reviewers at CR website are more like to offer negative reviews if their car models are criticized by CR; third, for the mixed online consumer reviews, the CRGOOD is positive and significant in both levels. Recall that consumer satisfaction level is not related for the mixed reviews, and we here find out that the t-value (t=6.236) of CRGOOD is the highest among all explanatory variables, which implies that the largest explanatory power of explaining mixed reviews come from CR's endorsement actions. These findings imply that reviewers who post mixed reviews are different from reviewers who either post positive or negative reviews in terms of their behaviors and motivations. One possible explanation is that this group of reviewers has more opinion leadership characteristics than other two groups, and therefore they are more likely to react to CR's endorsements.

Dynamic of Online Consumer Reviews

To examine the robustness of the above results, analysis can again be applied to each generation of car models, such as the analysis only for 2006 car models, the analysis only for 2005 car models and the analysis for 2004 to 2001 car models. Since we focus on each generation basis, and the dependent variables, the number of total online consumer reviews (TWOM), the number of positive online consumer reviews (PWOM), the number of negative online consumer reviews (NWOM) and the number of mixed online consumer reviews (MWOM), are counts of events, we can perform negative binomial regressions[11](Cameron, Trivedi and Chester 1998). Specially, the following models are estimated:

$$TWOM_i = \beta_0 + \beta_1 CS_i + \beta_2 CS_i^{\,2} + \beta_3 HIS_i + \beta_4 NEW_i + \sum_{i=5}^{13} \beta_i VehicleType \quad (10)$$

$$+ \beta_{14} CRGOOD_i + \beta_{15} CRBAD_i + \beta_{16} SALES_i + \varepsilon_i$$

$$PWOM_i = \beta_0 + \beta_1 CS_i + \beta_2 HIS_i + \beta_3 NEW_i + \sum_{I=4}^{12} \beta_i VehicleType + \beta_{13} CRGOOD_i + \beta_{14} CRBAD_i + \beta_{15} SALES_i + \varepsilon_i \quad (11)$$

$$NWOM_i = \beta_0 + \beta_1 CS_i + \beta_2 HIS_i + \beta_3 NEW_i + \sum_{I=4}^{12} \beta_i VehicleType + \beta_{13} CRGOOD_i + \beta_{14} CRBAD_i + \beta_{15} SALES_i + \varepsilon_i \quad (12)$$

$$MWOM_i = \beta_0 + \beta_1 CS_i + \beta_2 HIS_i + \beta_3 NEW_i + \sum_{I=4}^{12} \beta_i VehicleType + \beta_{13} CRGOOD_i + \beta_{14} CRBAD_i + \beta_{15} SALES_i + \varepsilon_i \quad (13)$$

We first fit negative binomial regressions for total online consumer reviews across three generations of car models: 2006, 2005 and 2004 or before. Table 9 presents the results and since this is for total online consumer reviews we can compare these results to the results from table 7. In general, we expect that a consistency exists between OLS regression models and negative binomial regression models.

First, we find that the CS is positive and significant but the CS^2 is not significant across three generations of car models[12]. Second, the HIS is negative and significant and the NEW is positive and significant across three generations of car models. These findings are exactly same with the findings from OLS regressions. However, the LUXURY and SMALL are not significant in negative binomial regression analysis[13]. Third, the CRGOOD is positive and significant across three generations of car models, which is exactly same with the finding from OLS regressions. Overall, negative binomial regressions yield very similar findings to these from OLS regressions for total online consumer reviews.

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[11] The CR online reviews platform started in Feb 2004. By that time, 2005 car models and 2006 car models haven't introduced to the market therefore there are no online consumer reviews for these models. A pooled negative binomial regression, similar to our first OLS regression in the disaggregated level, may not appropriate since 2006 car models and 2005 car models are given not equal opportunity/time being reviewed as 2004 car models or before 2004.

[12] This is similar to the OLS regression in the aggregated level and it is not consistent with OLS regression in the disaggregated level where both CS and CS^2 are significant. One possible reason is the sample size compared to 746 observations in the disaggregated level.

[13] The dependent variable in OLS regression is the density of online consumer reviews while the dependent variable in negative binomial regression is the number of online consumer reviews. This difference may account for some inconsistency between OLS regressions and negative binomial regression.

Table 9: Negative Binomial Regression on Number of Total Online Consumer Reviews for 2006 car Models, 2005 Car Models and 2004 to 2001 Car Models

	2006	2005	2004~2001
Intercept	2.481e+00(19.165)***	2.579e+00(17.144)***	2.198e+00 (21.490)***
CS	2.777e-02 (5.004)***	1.454e-02 (2.328)**	1.262e-02 (3.102)***
CS^2	2.855e-04 (0.879)	1.454e-04 (0.406)	-2.142e-04 (-0.823)
HIS	-3.121e-02 (-2.860)***	-4.217e-02 (-3.318)***	-3.310e-02 (-3.239)***
NEW	5.947e-01(4.542)***	4.126e-01 (3.203)***	4.066e-01 (4.529)***
PICKUP	1.120e-01(0.411)	-2.154e-01(-0.728)	-1.737e-01 (-0.906)
VAN	-1.134e-01(-0.496)	9.632e-02 (0.390)	4.234e-01 (2.490)**
SPORTS	-2.637e-01(-1.224)	-3.410e-01 (-1.359)	-3.381e-01(-2.055)**
LUXURY	5.823e-02 (0.415)	-9.393e-02 (-0.595)	-4.085e-02 (-0.398)
SMALL	7.389e-02 (0.329)	-9.228e-02 (-0.392)	-8.327e-02 (-0.530)
LARGE	-8.091e-02 (-0.327)	-2.995e-01 (-1.026)	8.470e-02 (0.371)
FAMILY	2.629e-02 (0.152)	8.861e-02 (0.434)	3.108e-01 (2.520)**
COUP	-7.873e-01(-1.560)	-8.468e-01(-1.522)	-1.258e+00 (-2.953)***
WAGON	9.658e-02 (0.467)	4.099e-02 (0.156)	2.049e-01 (0.893)
CRGOOD	3.100e-01(2.395)**	6.659e-01 (4.391)***	5.753e-01 (5.952)***
CRBAD	1.154e-01(0.713)	-1.776e-01 (-0.942)	-6.215e-03 (-0.052)
SALES	6.756e-06 (8.763)***	8.484e-06 (9.418)***	5.846e-06 (12.405)***
AIC	1288.3	1247.8	3239.8
2xlog-likelihood	-1252.277	-1211.843	-3203.815
N=	170	155	441

Notes: 1. *** P<0.01; **P<0.05; *P<0.1
2. t-statistics are shown in parentheses.
3. The dependent variable is number of online consumer reviews for a car model

Table 10 presents the negative binomial regressions results on the three dependent variables: the number of positive, mixed and negative online consumer reviews, across three generations of car models: 2006, 2005 and 2004 to 2001 car models. First, regarding the positive online consumer reviews, the CS is positive and significant across three generations of car models. In terms of the negative online consumer reviews, the CS is negative and significant just for 2004 to 2001 car models, but insignificant for 2006 or 2005 car models. Recall in the previous OLS regression analysis, we have only partial evidence to support the negative relationship between the negative online consumer reviews and consumer satisfaction level. The evidence here seems to give an idea that the consumer satisfaction level has more influence on the negative online consumer reviews for the “old” generation car models versus for “new” generation car models. This makes sense because the older the car is, the higher likelihood having quality problems, and therefore online consumer reviewers are more likely to offer negative reviews because they dissatisfy with their car models. In terms of mixed reviews, the CS is insignificant for 2006 car models and 2004 to 2001 car models, which is exactly same with the findings from OLS regressions.

Second, the HIS is negative and significant in the models for which regress on positive and mixed reviews but not on negative reviews and this is across three generations of car models; the NEW is positive and significant in the models for which regress on the three dependent variables and this is across three generations of car models. Again, these findings are same with the findings yielded by OLS regressions. The LUXURY and SMALL are insignificant, which are not consistent with the findings from OLS regressions. Third, in terms of the positive online consumer reviews, the CRGOOD is positive and significant across three generations of car models; in terms of the negative online consumer reviews, the CRBAD is positive and significant across three generations; for the mixed online consumer reviews, the CRGOOD is positive and significant across the three generations as well. These findings are exactly same with findings from OLS regressions in both the disaggregated and aggregated level. Overall, we can conclude that CR’s endorsement actions influence both volume and valence of online WOM at CR website. Our following analysis is going to examine whether or not this is the case at other websites, such as Edmunds.com, and therefore we are able to generalize that TPO endorsements or reviews indeed influence online WOM activities.

Table 10: Negative Binomial Regression on Number ofPositive / Mixed / Negative Online Consumer Reviews For 2006 Car Models and 2005 Car Models

	2006 car models			2005 car models		
Variable	Positive WOM	Mixed WOM	Negative WOM	Positive WOM	Mixed WOM	Negative WOM
Intercept	-4.112e-01(-1.119)	8.627e-01(1.770)	-6.580e-01(-1.055)	5.875e-01 (1.369)***	2.017e+00 (5.037)***	-4.215e-01 (-0.645)
CS	4.029e-02 ([illegible].010)***	9.184e-05 (0.012)	2.472e-03 (0.252)	2.556e-02 (3.821)***	-1.386e-02 (-2.181)**	-4.404e-03 (-0.428)
HIS	-3.650e-02 (-3.223)***	-3.154e-02 (-2.048)**	1.281e-02 (0.658)	-4.348e-02 (-3.163)***	-3.907e-02(-2.867)***	4.870e-03 (0.222)
NEW	4.965e-01 (3.721)***	8.455e-01(4.862)***	5.233e-01(2.404)**	3.597e-01 (2.582)***	4.571e-01(3.543)***	3.414e-01(1.640)
PICKUP	1.430e-02 (0.050)	5.208e-01(1.527)	-2.413e-01(-0.474)	-2.252e-01 (-0.712)	-4.838e-02 (-0.176)	-1.032e+00 (-1.716)*
VAN	-6.481e-02 (-0.282)	-1.775e-01(-0.605)	4.568e-01(1.417)	4.734e-02 (0.185)	1.478e-01(0.673)	2.755e-01 (0.839)
SPORTS	-2.763e-01(-1.246)	-9.073e-02(-0.290)	-8.979e-01(-1.702)*	-2.864e-01(-1.063)	-4.655e-01(-1.568)	-1.101e-01(-0.247)
LUXURY	5.099e-02 (0.354)	-2.302e-02 (-0.116)	1.581e-01(0.641)	-2.985e-02 (-0.176)	-2.834e-01(-1.654)*	-9.580e-02 (-0.335)
SMALL	3.708e-02 (0.159)	2.005e-01 (0.679)	5.931e-02(0.166)	-6.350e-02 (-0.250)	-2.078e-01(-0.920)	-2.164e-01(-0.608)
LARGE	-7.471e-02 (-0.295)	-7.646e-02(-0.216)	3.303e-01(0.796)	-2.344e-01 (-0.749)	-3.542e-01(-1.162)	-3.400e-01(-0.612)
FAMILY	6.710e-02 (0.377)	2.444e-02 (0.106)	-2.999e-01(-0.958)	1.327e-01(0.605)	-5.923e-02 (-0.299)	-1.862e-01(-0.567)
COUP	-8.872e-01(-1.642)	-3.643e-01(-0.482)	-3.699e+01(-7.8e-07)	-5.861e-01(-0.983)	-1.654e+00 (-1.548)	-3.692e+01 (-7.73e-07)
WAGON	8.206e-02 (0.389)	6.274e-02 (0.224)	-3.346e-01(-0.800)	1.052e-02 (0.037)	2.232e-03 (0.009)	2.252e-01 (0.515)
CRGOOD	2.262e-01(1.715)*	6.989e-01(3.931)***	3.548e-01(1.556)	6.080e-01(3.781)***	1.011e+00 (6.547)***	2.937e-01(1.117)
CRBAD	1.302e-01 (0.766)	6.930e-03 (0.030)	5.776e-01(2.164)**	-3.877e-01(-1.849)*	-8.391e-02 (-0.415)	8.991e-01(3.304)***
SALES	6.114e 06(7.729)***	7.365e 06(7.293)***	5.513e 06(4.527)***	8.187e 06 (8.429)***	8.433e 06 (9.926)***	8.573e 06 (6.518)***
AIC	1167.5	870.83	540.29	1144.0	823.35	482.92
2xlog-likelihood	-1133.496	-836.831	-506.293	-1109.964	-789.354	-448.923
N=	170	170	170	155	155	155

Notes: 1. *** P<0.01; **P<0.05; *P<0.1
2. t-statistics are shown in parentheses.
3. The dependent variables are number of positive / mixed / negative consumer reviews for a car model

Table 10 (Continued): Negative Binomial Regression on Number of Positive/Mixed/Negative Online Consumer Reviews for 2004 To 2001 Cars Models

	2004~2001 car models		
Variable	Positive WOM	Mixed WOM	Negative WOM
Intercept	3.023e-01(-1.015)	1.153e+00(3.644)***	8.918e-01(1.917)
CS	2.711e-02 (6.290)***	2.073e-03 (0.450)	-1.493e-02 (-2.187)**
HIS	-3.378e-02 (-3.132)***	-3.693e-02 (-3.151)***	-1.543e-02 (-0.902)
NEW	4.127e-01 (4.370)***	2.502e-01(2.469)**	6.302e-01 (4.448)***
PICKUP	-2.269e-01(-1.098)	-1.727e-01(-0.830)	-4.572e-01 (-1.412)
VAN	2.287e-01(1.278)	5.662e-01(3.104)***	5.174e-01 (2.043)**
SPORTS	-3.262e-01(-1.829)*	-5.215e-01(-2.581)***	-8.796e-04 (-0.003)
LUXURY	1.552e-03(0.014)	-2.310e-01(-1.925)*	2.758e-02 (0.154)
SMALL	-1.391e-01(-0.834)	-3.720e-02 (-0.213)	1.655e-01 (0.664)
LARGE	1.296e-01(0.540)	-3.298e-03(-0.013)	-7.596e-01 (-1.447)
FAMILY	2.600e-01(2.012)**	2.998e-01 (2.212)**	2.625e-01 (1.298)
COUP	-8.450e-01(-1.772)*	-2.119e+00 (-2.727)***	-1.257e+00 (-1.736)*
WAGON	3.092e-01 (1.306)	1.122e-01 (0.438)	1.101e-01(0.288)
CRGOOD	7.462e-01(7.416)***	4.268e-01(3.846)***	-3.161e-01 (-1.783)*
CRBAD	-2.012e-01(-1.505)	-1.336e-01(-0.947)	6.467e-01 (3.600)***
SALES	5.192e-06 (10.555)***	6.316e-06(12.288)***	3.761e-06 (5.074)***
AIC	2690.9	2430.7	1432.2
2xlog-likelihood	-2656.943	-2396.654	-1398.187
N=	441	441	441

Notes: 1. *** P<0.01; **P<0.05; *P<0.1
2. t-statistics are shown in parentheses.
3. The dependent variables are number of positive/mixed/negative consumer reviews for a car model

TPO Endorsements or Reviews on Online Consumer Reviews

Recall that we also collect the number of total online consumer reviews (EDTWOM) and Edmunds endorsements or reviews (EDGOOD) for 2005 car models[14] from Edmunds.com. We choose it because Edmunds and CR are comparable in many ways. For instance, both websites are offering straightforward endorsements (e.g. Editor's Most Wanted or Consumers Most Wanted from Edmunds and Consumer Reports' Good Bet or Bad Bet); both websites contain their own online WOM platforms, which allow their members post reviews. We apply the same assumptions that previously work for CR to Edmunds: 1) we assume that before an online consumer reviewer post a review at Edmunds, he/she has exposed to Edmunds' endorsements or reviews; 2) Edmunds and Consumer Reports only provide technology maintenances of their online WOM platforms but don't manipulate online WOM activities.

[14] We choose 2005 car models because we observe more total online consumer reviews than other generations models at both CR and Edmunds websites.

Since EDTWOM is a count of events, we fit a negative binomial regression:

$$EDTWOM_i = \beta_0 + \beta_1 CS_i + \beta_2 CS_i^{\,2} + \beta_3 HIS_i + \beta_4 NEW_i + \sum_{i=5}^{13} \beta_i VehicleType \quad (14)$$
$$+ \beta_{14} CRGOOD_i + \beta_{15} CRBAD_i + \beta_{16} EDGOOD + \beta_{17} SALES_i + \varepsilon_i$$

Table 11 presents the negative binomial regressions results on the number of total online consumer reviews for 2005 car models at CR and Edmunds. At Edmunds website, we find that the CS and CS^2 are insignificant, which indicates that online WOM activities occurring at Edmunds is not related to consumer satisfaction. This finding is not totally surprise if we begin to consider the demographic factors of two websites. Consumer reviewers at CR are possible quality sensitive population, whereas reviewers at Edmunds may be car fans population. Considering the fact that consumer satisfaction is more closely related to quality or reliability other than fancy body or acceleration in which car fans population are most interested, it is not surprise to observe that two populations have different online WOM behaviors. The HIS is negative and significant, and the NEW is positive and significant at Edmunds website, which are exactly same with findings from CR. Our major interest is TPO endorsements' influence on online WOM. At CR website, we find that CRGOOD is positive and significant but EDGOOD is insignificant, whereas at Edmunds website EDGOOD is positive and significant but CRGOOD is insignificant. These findings suggest that CR's endorsement actions stimulate online WOM activities only at CR website whereas Edmunds' endorsement actions stimulate online WOM activities at Edmunds website. An important implication is that TPO endorsements or reviews indeed directly influence online WOM other than predict online WOM[15]

Table 11: Negative Binomial Regression on the Number of Total Online Consumer Reviews for 2005 car Models at CR and Edmunds

Variable	CR	Edmunds
Intercept	2.589e+00 (17.144)***	4.372e+00 (30.914)***
CS	1.418e-02 (2.267)**	1.799e-03 (0.303)
CS^2	1.508e-04 (0.422)	4.538e-04 (1.347)
HIS	-4.356e-02 (-3.365)***	-5.290e-02 (-4.393)***
NEW	3.986e-01 (3.068)***	5.064e-01 (4.154)***
PICKUP	-2.256e-01 (-0.763)	-3.448e-01 (-1.263)
VAN	1.013e-01 (0.411)	-3.979e-01 (–1.717)*
SPORTS	-3.476e-01 (-1.388)	-1.124e-01 (-0.496)
LUXURY	-1.138e-01 (-0.715)	5.864e-02 (0.397)
SMALL	-9.570e-02 (-0.407)	-1.324e-01 (-0.596)
LARGE	-2.872e-01(-0.987)	-1.506e-01 (-0.560)
FAMILY	1.086e-01 (0.523)	1.632e-01 (0.833)
COUP	-8.507e-01 (-1.531)	-6.426e-02 (-0.142)
WAGON	1.726e-02 (0.065)	1.139e-01 (0.455)
CRGOOD	6.664e-01 (4.400)***	1.587e-01(1.097)
CRBAD	-1.721e-01 (-0.914)	-2.055e-02 (-0.121)
EDGOOD	1.017e-01 (0.658)	3.315e-01 (2.302)**
SALES	8.335e-06 (9.035)***	5.869e-06 (6.711)***
AIC	1249.4	1700.7
2xlog-likelihood	-1211.410	-1662.677
N=	155	154

Notes: 1. *** P<0.01; **P<0.05; *P<0.1
2. t-statistics are shown in parentheses.
3. The dependent variable is number of total online consumer reviews for a car mod

[15] As a predictor, TPO endorsements are able to capture information of reliability, quality, performance, values, functions and even customer satisfaction of a car model, therefore precisely predict which car model will have more online WOM activity or less WOM activity.

Managerial Implications and General Discussion

This study makes use of online WOM data for automobiles to examine the antecedents of online WOM, the multiple factors that either stimulate positive or create negative online WOM, the dynamic pattern of online WOM activities, and the unique, untested influence of TPO endorsements or reviews' on both volume and valence of online WOM. The study contributes to the growing online WOM literature, automobile industry and potentially buzz marketing management for durable goods, such as computers, digital camera or other consumer electronics. Managerial speaking, we believe the findings of this study may be generalized to consumer electronics because automobiles and consumer electronics share many same attributes: 1) WOM plays an important role in the purchasing process; 2) consumers are very sensitive to the quality; 3) manufactures regularly innovate products and technologies; 4) consumers go to TPO websites[16] for product information. The analysis provides some evidence to support a U-shape relationship between consumer satisfaction and online WOM. Although there is a clear positive relationship between consumer satisfaction and positive online WOM, a negative relationship between consumer satisfaction and negative online WOM is equivocal. Even more interestingly, we demonstrate that mixed online WOM is generally independent of consumer satisfaction, and online WOM is also independent of consumer satisfaction at Edmunds website. All these findings suggest that online WOM adopts a more complex pattern than offline WOM. It may be difficult to image that a regular consumer who are neither satisfied nor dissatisfied with his/her product has motivations to spread WOM among his/her friends. However, a same consumer is likely to spread mixed WOM online simply because he/she wants to show his/her expertise in this product domain or he/she sees other people are offering reviews. A managerial implication of these findings is that improving consumer satisfaction is still a strategy to increase online WOM activities considering the fact that online WOM is dominantly positive in nature.

This study provides the solid evidence that the newness of a product stimulates online WOM activities about the product. The newness has two meanings in this study: 1) a short history in the market; 2) a new model or a new design to an "old" model. An important implication for managers is that innovation is an effective strategy to create online WOM. Companies should regularly re-design their products, advance their technologies, and introduce new products. Telling consumers the new attributes or technologies about their "old" products may be able to create some sort of newness perception and therefore increase online WOM. One of major contributions of this study to online WOM literature is that we find TPO endorsements or reviews influence online WOM. Specially, positive TPO endorsements or reviews stimulate positive online WOM, whereas negative TPO reviews stimulate negative online WOM. An important managerial value of this finding is that companies can manage TPO endorsements or reviews in such way to maximize positive online WOM. For instance, companies can run online advertising campaigns to spread good news, especially the websites that contain online WOM platforms. Second, since many online retailers also allow customers to offer reviews, showing TPO endorsements or reviews at retailer websites may be able to create more positive online WOM. We conclude this article by discussing limitations of this study as well as directions for future studies. We mainly analyze online WOM data from Consumer Reports website. Therefore, sampling biases could be an issue. An alternative way is to collect online WOM data from several major automobiles websites and analyze robustness of online WOM, but data collection process can be a difficult task. Second, an online reviewer offer a review simply because he/she sees many reviews and thus want to add his/her opinions. Another possible case is that an online reviewer's attitude is not independent of other's attitude. We don't have such data in this study to enable us to examine this potential relationship. These issues bring us an important question: "how similar the online WOM is to offline WOM?" One argument is that online WOM is a proxy of offline WOM. However, online reviewers can be a tiny subset of general population who basically behave differently. Our study has no answer for this question. Further studies on this topic would be valuable.

[16] Consumers go to websites, such as PC WORLD, CNET, PC Magazine to search third-party organization endorsements or product reviews for computers, digital camera or other consumer electronics.

References

Anderson, Eugene (1998), “Consumer Satisfaction and Word of Mouth,” Journal of Service Research, 1(1), 5-17.

Arnett, Dennis B., Steve D. German, and Shelby D. Hunt. (2003), "The Identity Salience Model of Relationship Marketing Success: The Case of Nonprofit Marketing," Journal of Marketing, 67 (April), 89-105.

Arndt, Johan (1967), “The Role of Product-Related Conversation in the Diffusion of a New Product,” Journal of Marketing Research, 4 (August), 291-143.

Bao, Tong and Chang, Tung-lung Steven (2014), "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.

Bearden, W. O., and M.J. Etzel (1982), “Reference Group Influence on Product and Brand Purchase Decisions,” Journal of Consumer Research, 9(2), 183-194.

Black, John S. (1982), “Opinion Leaders: Is Anyone Following?” Public Opinion Quarterly, 46(Summer), 169-176.

Basuroy, Suman, Subimal Chatterjee and Abraham Ravid (2003), “How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets,” Journal of Marketing, 67(October), 103-117.

Brown, Jacqueline Johnson and Peter H. Reingen (1987), “Social Ties and Word-of-Mouth Referral Behavior,” Journal of Consumer Research, 14 (December), 350-362.

Brown, Tom J., Thomas E. Barry, Peter A. Dacin and Richard F. Gunst (2005), “Spreading the Word: Investigating Antecedents of Consumers’ Positive Word-of-Mouth Intentions and Behaviors in a Retailing Context,” Journal of the Academy of Marketing Science, 33(2), 123-138.

Chan, Kenny K. and Shekhar Misra (1990), “Characteristics of the Opinion Leader: A New Dimention,” Journal of Advertising, 19(3), 53-60.

Chen, Yubo and Jinhong Xie (2005), “Third-Party Product Review and Firm Marketing Strategy,” Marketing Science, 24(2), 218-240.

Chevalier, Judith and Dina Mayzlin (2006), “The Effect of Word of Mouth on Sales: Online Book Reviews,” Journal of Marketing Research, 43(3), 345-354.

Day, G.S. (1971), “Attitude Change, Media, and Word of Mouth,” Journal of Advertising Research, 11(6), 31-40.

Dean, Dwane Hal (1999), “Brand Endorsement, Popularity, and Event Sponsorship as Advertising Cues Affecting Consumer Pre-purchase Attitudes,” Journal of Advertising, 28(Fall), 1-12.

______and Abhijit Biswas (2001), “Third-Party Organization Endorsement of Products: An Advertising Cue Affecting Consumer Prepurchase Evaluation of Goods and Services,” Journal of Advertising, 30, 41-57.

De Silva, Indra (1998), “Consumer Selection of Motion Pictures,” in The Motion Picture Mega-Industry, Barry R. Litman, ed. Needham Heights, MA: Allyn Bacon, 144–71.

Dellarocas, Chrysanthos and Ritu Narayan (2006), “A Statistical Measure of a Population’s Propensity to Engage in Post-Purchase Online Word-of-Mouth,” Statistical Science, 21(2), 277-285.

Eliashberg, Jehoshua and Steven M. Shugan (1997), “Film Critics: Influencers or Predictors?” Journal of Marketing, 61 (April), 68–78.

Feng, J., Wang, K.-Y., Peracchio, L. (2008), “How Third-party Organization (TPO) Endorsement Advertising Works: Do Consumers Perceive TPO Endorsement as Signals of Quality?” Advances in Consumer Research, 35, 616-623.

Godes, David and Dina Mayzlin (2004), “Using Online Conversations to Study Word-of Mouth Communication,” Marketing Science, 23 (4), 545–60.

Jedidi, Kamel, Robert E. Krider, and Charles B. Weinberg (1998), “Clustering at the Movies,” Marketing Letters, 9 (4), 393–405.

Katz, Elihu and Paul F. Lazarsfeld (1955), Personal Influence. Glencoe, IL: Free Press.

Klein, Lisa R. and Gary T. Ford (2003), “Consumer Search for Information in the Digital Age: An Empirical Study of Prepurchase Search For Automobiles,” Journal of Interactive Marketing, 17(3), 29-49.

Litman, Barry R. (1983), “Predicting the Success of Theatrical Movies: An Empirical Study” Journal of Popular Culture, 17 (Spring), 159–75.

——— and Hoekyun Ahn (1998), "Predicting Financial Success of Motion Pictures," in The Motion Picture Mega-Industry, Barry R. Litman, ed. Needham Heights, MA: Allyn Bacon, 172–97.

——— and L.S. Kohl (1989), "Predicting Financial Success of Motion Pictures: The '80s Experience," Journal of Media Economics, 2, 35–50.

Liu, Yong (2006), Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," Journal of Marketing, 70(July), 74-89.

Montgomery, D., and A. Silk. (1971), "Clusters of Consumer Interest and Opinion Leaders' Spheres of Influence," Journal of Marketing Research, 8(3), 317-321.

Pitt, Leyland F , Pierre R Berthon, Richard T Watson, George M Zinkhan (2002), "The Internet and the birth of real consumer power," Business Horizons, 45(4), 7-14.

Prag, Jay and James Casavant (1994), "An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry," Journal of Cultural Economics," 18, 217–35.

Ratchford, lee and Talukdar (2003) Ratchford, Brian, Myung-Soo Lee and Debabrata Talukdar (2003), "The Impact of The Internet on Information Search for Automobiles," Journal of Marketing Research, 40(2), 193-209.

Ravid, S. Abraham (1999), "Information, Blockbusters, and Stars: A Study of the Film Industry," Journal of Business, 72 (October), 463–92.

Richins, Marsha L. (1983), Negative Word-of-Mouth by Dissatisfied Consumers: A Pilot Study." Journal of Marketing, 47 (Winter), 68-78.

_____ and Teri Root-Shatter. (1988), "The Role of Involvement and Opinion Leadership in Consumer Word-of-Mouth: An Implicit Model Made Explicit." In Advances in Consumer Research. Vol. 15. Ed. Michael J. Houston. Provo. UT: Association for Consumer Research, 32-36.

Sochay, Scott (1994), "Predicting the Performance of Motion Pictures," Journal of Media Economics, 7 (4), 1–20.

Swan, J.E. and Oliver, R.L. (1989) Postpurchase communications by consumers. Journal of Retailing, 65(2), 516–33.

Thurau, Thorsten Henning, Kevin P. Gwinner, Gianfranco Walsh and Dwayne D.

Gremler (2004), "Electronic Word-of-Mouth Via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on The Internet," Journal of Interactive Marketing, 18(1), 38-52.

Wallace, W. Timothy, Alan Seigerman, and Morris B. Holbrook (1993), "The Role of Actors and Actresses in the Success of Films," Journal of Cultural Economics," 17 (June), 1–27.

Westbrook, Robert A. (1987), "Product/Consumption-Based Affective Responses andPostpurchase Processes," Journal of Marketing Research, 24 (August), 258-270.

Cameron, A. C., Trivedi, P. K., Chester, A. (1998) Regression Analysis of Count Data.Cambridge University Press.

Baba Shiv, Ziv Carmon, and Dan Ariely (2005), "Placebo Effects of Marketing Actions: Consumers May Get What They Pay For," Journal of Marketing Research, Vol. XLII (November), 383–393