Online Opinions for Automobiles: A Dynamic Perspective

Jie Feng
SUNY Oneonta

Online word of mouth (WOM) has become increasingly important in consumer purchasing decisions. It has the potential to be a new sort of marketing communication mix. Scion, for example, held "ride-and-drive" events in which young drivers were encouraged to write messages on social networking sites. The campaign was a massive success. On the other hand, When Chevrolet announced a Web contest to develop advertising for the Chevrolet Tahoe, the campaign quickly spiraled out of hand, resulting in numerous negative messages regarding the vehicle's poor gas mileage. Understanding the mechanism is critical to the success of an online WOM campaign. This mechanism is divided into two decisions: posting decisions and assessment decisions. The latter process—the individual reviewer's rating of her product—is the topic of this study.

Keywords: online word of mouth, online rating, online review, social media

INTRODUCTION

Online word of mouth (WOM) has been playing an increasingly significant role in consumer purchase decisions. According to a recent survey (Opinion Research Corporation, 2009), 84 percent of Americans state that online customer evaluations influence their decision to purchase a product or service. Prior studies illustrate that a variety of aspects of online WOM influence sales. For example, Godes and Mayzlin(2004) find that the dispersion of conversations among different newsgroups has significant explanatory power on TV viewership. Liu (2006) demonstrates that the volume of WOM is a powerful predictor of sales of movie box office revenue; Chevalier and Mayzlin (2006) find that the valence of online WOM has a significant effect on the sales of books. In addition to the studies focusing on the effect of online WOM on sales, another stream of recent studies suggests that firms may strategically create, control, and manage online WOM to influence consumers' purchase decisions (i.e., Dellarocas 2003; Godes, et al., 2005; Dellarocas 2006; Mayzlin 2006; Godes and Mayzlin, 2009).

Accordingly, the automobile industry has been utilizing this seemingly "free" promotional tool. For instance, the Scion held "ride-and-drive" events asking young drivers to post messages on social networking sites such as MySpace and YouTube. Thanks to such innovative marketing, the Scion model launched by Toyota in 2003 reached sales of over 176,000 cars by 2007 (Forbes 2007). Another automobile brand emphasizing WOM advertising is the Ford Fiesta (Forbes 2009). Ford provided the brand to one hundred consumers to test drive and post their comments on an online site. Ford's objective is to build brand awareness, as with traditional advertising campaigns, but the cost of this WOM campaign is "a fraction of a typical marketing and advertising campaign" (Forbes 2009). However, this new promotional tool is not without risks for marketers. Online WOM marketing can easily backfire. For example, when Chevrolet launched a Web contest to create ads for Chevrolet Tahoe, the campaign was soon out of control. Many individuals created negative videos about its abysmal gas mileage and uploaded them onto YouTube (Armstrong and Kotler, 2009).

The cases discussed previously illustrate both opportunities and challenges to firms. On the one hand, online WOM can serve as a new type of marketing communication mix and work as free “sales assistants” (Chen and Xie, 2008). On the other hand, it can turn against firms when the tone and content become negative. The key to the success of such a campaign is to understand the mechanism of online WOM contributions (Dellarocas and Narayan 2007; David and Silva 2009). This mechanism, according to Moe and Schweidel (2009), could be categorized into two decisions: a posting decision (why people post ratings and reviews) and an evaluation decision (what influences the valence of the review). In this study, we focus on the latter process—the individual reviewer’s rating of her product.

An individual reviewer’s rating can be jointly determined by two forces: her independent evaluation of the product and online opinions from others (Moe and Schweidel 2009; Moe and Trusov 2009; Moon, Bergey and Lacobucci 2010). A reviewer’s independent evaluation of her product is shaped by her consumption experience and her characteristics (i.e. age). Her consumption experience can be further influenced by several factors: product attributes (i.e. quality, style, design, and features), price, brand image, and how she uses the product (i.e. light usage or intensive usage). Online opinions from others refer to two information sources: previously posted reviewers’ ratings (Moe and Schweidel 2009; Moe and Trusov 2009) and expert ratings (Moon, Bergey, and Lacobucci 2010). Both information sources are easily available to the reviewer on many review websites and they can revise the reviewer’s independent evaluation either upward or downward.

To investigate the review’s rating, the automobile industry provides an ideal test bed for our analysis. First, online WOM behavior is likely to be high for automobiles since this is a category that consumers would like to research and discuss online. Comscore (2007) finds that 78% of those people reading online reviews of cars by other consumers say that the reviews influence their car buying decision. Second, a majority of prior studies relating to online WOM’s focus on low-cost entertainment goods, such as movies, TV programs, and books. The findings from these studies may not be generalizable to durable goods. Godes and Mayzlin (2004) therefore recommend that more investigation of online WOM for expensive goods should be undertaken. Third, we chose automobiles for their economic importance, because the automobile business represents over 3% of gross domestic product (Srinivasan et al. 2008). Last, but not least, as we discussed previously, the automobile industry is shifting its promotions from traditional mass media to online WOM campaigns. To be successful with such campaigns, however, it is important to understand their workings.

One characteristic that distinguishes online WOM for an automobile from the online conversation for a movie is that the latter lasts for a much shorter time during the few weeks following opening day and then soon diminishes (Liu 2006) whereas online reviews for a car model could last for several years since its launch. Thus, for instance, we can observe many reviews for the 2005 Honda Accord in early 2005 and also some reviews for the same model occurring in late 2006. In fact, on sites like Edmunds.com, we can observe recently posted reviews of the 2005 Honda Accord almost five years after its release. This long-term nature of word of mouth for automobiles raises the following question: would the factors influencing online opinions when they are stated soon after the purchase be different from the factors when they are stated long after the purchase?

In this study, we focus on two major product attributes for an automobile: quality/reliability and design/performance. According to J.D.Power & Associates, “There are two schools of thought among consumers in determining which new-vehicle model to buy. Many consumers are looking for a painless, trouble-free ownership experience. …However, there is a large group of buyers who are most interested in things like comfort, style, and performance (2006).” Quality/reliability and design/performance can also be interpreted as utilitarian and hedonic aspects of a product that play an important role in consumer choice (Chernev 2004).

We reason that if a reviewer engages in offering an online rating soon after she purchases the car, her opinion is more likely to revolve around the car’s design/performance. This is because she has very limited information about the car's reliability or quality consistency at this stage. However, she can evaluate her car based on her observation and feeling toward the car's appearance, interior, and exterior design and driving experience. On the other hand, as the reviewer uses the car for a longer period, she may be able to develop a deeper understanding of her car. She may experience engine or transmission failures or other mechanical problems. Therefore, we reason that if a reviewer offers an online rating of her car after using it for some time, her opinion is more likely to be shaped by the car's quality/reliability.

Using online opinion data from the review website of Consumer Reports and other multiple data sources (i.e., automobile attribute data from J.D. Power and Associates), we fit ordinal-logit models and find that the design/performance of a car influences the early stage of online opinions, but its influence decreases over time, whereas the quality of a car influences the late stage of online opinions as the influence of the quality of a car on online opinions increases over time.

Another important finding is regarding social influences of others. We find that positive recommendations by experts of Consumer Reports are positively related to online opinions while negative recommendations are negatively related to online opinions. The magnitude of negativity influence is larger than the magnitude of positivity influence. We also find that online opinions become more negative as volume increases and the closest previous post has the largest influence on the current online rating.

From a managerial perspective, we believe that an online WOM campaign could benefit from the key findings of this study. One unique feature of online WOM campaigns is that firms initiate it, but consumers implement it (Godes and Mayzlin 2009; Godes et al 2005). We, therefore, suggest that automobile manufacturers should carefully select the best car models to be promoted with word-of-mouth marketing. Since the goal of this type of campaign is to create and maximize positive online conversations about a promoted car immediately after its release, a well-designed model with excellent driving performance (i.e., better acceleration) will be a better choice than a car with excellent quality and reliability but not outstanding design. In particular, we suggest that auto firms avoid promoting gas-guzzling cars using online WOM marketing because negative online opinions are more likely to occur.

The rest of the manuscript is organized as follows. In the following section, we provide a brief overview of the literature. Next, we describe our data and the variables that we use in our research. We follow this with a section describing our model and our approach to the empirical analysis. The next section presents and discusses our findings. The paper concludes with a section summarizing our findings and their managerial and future research implications.

LITERATURE REVIEW AND THEORETICAL DEVELOPMENT

It is believed that online WOM can play two roles: an informative role to enhance consumer awareness and a persuasive role to help form attitudes towards the product. The volume of WOM, or the number of reviews posted, is traditionally treated as a measure of the informative role and the rationale is that the greater the volume of WOM of a product, the more people may hear about it and hence the higher would be the sales. Studies suggest that the volume of online WOM is positively associated with sales (i.e., Liu 2006; Duan, Gu, and Whinston 2008). The valence of WOM, measured as the average rating, or percentage of positive/negative reviews, is traditionally viewed as the evaluation of a product. It is straightforward in that positive WOM enhances purchase intentions, while negative WOM reduces them. Several prior studies support this view. Chevalier and Mayzlin (2006) find that positive reviews of a book increase the sales of the book, whereas negative reviews depress sales. The impact of negative reviews on sales is found to be greater than the impact of positive reviews on sales. Dellarocas, Zhang, and Awad (2008) use a Bass diffusion model to predict movie sales. They find that the average valence of user reviews can help explain coefficient q of internal influence (that relates to consumer WOM) and coefficient p of external publicity. Clemons, Gao, and Hitt (2006) examine online opinions of sales for the craft beer category. They find that the average rating and variance of rating (not volume) affect sales growth and the most positive quartile of reviews have the greatest effect on predicting sales growth. Another study by Moe and Trusov (2009) separates the rating effect influenced by social dynamics from the baseline rating or the unbiased and independent evaluation of the product. They find that both parts of the ratings affect sales and that the effect of the baseline rating is larger than the effect of social dynamics.

As shown in Moe and Trusov's study, online ratings can be decomposed into a baseline rating and contribution of social influence. A baseline rating reflects a reviewer's evaluation of a product from his/her own experience with the product and is thus independent of others' evaluations. On the other hand, social influence captures the interdependent nature of the online rating because the rating an individual posts for a product may be affected by the previously posted ratings. The nature of interdependence of online ratings clearly distinguishes them from customer satisfaction where an individual's evaluation is not known to others and the motivation is not to enhance self-image or altruism (Hennig-Thurau et al. 2004). This means that online opinions may share some similarities with customer satisfaction, but also have their unique mechanism that we need to explore further.

As mentioned previously, the context of our investigation is online opinions on automobiles. Several popular sites, such as Yahoo, MSN, Edmunds, and Consumer Reports, provide automobile online WOM platforms where online consumer reviewers can post reviews of their cars. Consumers who wish to post reviews on the website first need to choose the specific car, in terms of the make, model, and year they own and wish to review. They can then rate the car using a scale, such as, 5='love it', 4='pretty good', 3='Ok', 2='not so hot' and 1='hate it'. They then can write detailed reviews, such as their driving experience, the comfort of the car, and any other overall comments and recommendations.

In this paper, we focus on the rating posted by each reviewer. One aspect of consumer ratings of cars is that some reviewers offer reviews and ratings within a short duration of the purchase while others do so following extended use of the car. We propose that this difference in the timing of online WOM has critical implications for this online opinion.

A consumer's evaluation of a car depends on the car's attributes and how he/she uses the car. Many automobile attributes are assumed to be related to this evaluation process and, in this paper, we focus on quality/reliability and design/performance. In the narrowest sense, quality can be defined as "freedom from defects" or "things that have not gone wrong" (Armstrong and Kotler, 2009). Design/performance means appearance, body-style, layout, and driving performance that can "excite and delight" car owners. We argue that consumers rely on both design/performance and quality/reliability to evaluate the car, but they may place different levels of importance on these two attributes depending on how long they have owned the car.

When consumers just purchase and experience a new car, they typically have limited knowledge about the car they own. Nevertheless, consumers may be able to quickly feel excited about its appearance, design, and driving performance. For example, a new car owner may be delighted when car designers add a luxury interior, GPS, or video equipment to the car model that is beyond her/his expectations. Therefore, if consumers engage in product discussions soon after they purchase the new car, they are more likely to react too easily observable attributes such as design or aesthetic appeal. Online opinions from such consumers are more likely to revolve around design/performance.

On the other hand, as they experience the car for a longer period, consumers may be able to develop a deeper understanding. They may also experience engine or transmission failures, and other mechanical problems, or they may have no problems at all. In the meanwhile, consumers' excitement toward the design of the car may erode as time goes by. We expect that both tendencies, a greater understanding of the car's mechanical functions and less interest in its superficial appearance, lead consumers to rely more on quality/reliability when evaluating the car they own. Therefore, if consumers discuss the car after using it for some time, their evaluation and discussion of the product with other consumers is more likely to focus on quality/reliability. Online opinions from such consumers are thus more likely to be related to quality/reliability.

In summary, we expect that an individual reviewer's rating toward his/her car is related to the design/performance and quality/reliability of the car. However, reviewers weigh the design/performance and the quality/reliability differently when they offer online opinions. More specifically, the importance of the design/performance decreases over time, whereas the importance of quality/reliability increases over time. This means that "early online opinions" (occurring soon after consumers use the car) are primarily shaped by the design/performance of the car while "delayed online opinions" (occurring long after consumers experience the car) are primarily shaped by the quality/reliability of the car.

DATA

Our data were obtained from two sources: the online sites of Consumer Reports magazine (www.consumerreports.org) and J.D. Power and Associates (www.jdpower.com). More specifically, we collected 30,168 individual reviews of car ratings posted between 03/04/2004 to 06/29/2008 for 1959 car models, ranging from 2000 car models to 2008 car models from Consumerreports.org. We also collected reviewers' characteristics and the date of offering the rating, from www.consumerreports.org. Automobile attribute data were obtained from www.jdpower.com.

Online Opinions

We collected each reviewer's rating of his/her car from the online site of Consumer Reports. An individual reviewer can rate his/her car based on a scale, such as 5 stars=love it, 4 stars=pretty good, 3 stars=Ok, 2 stars=not so hot and 1 star=hate it. We chose Consumer Reports as the source of online WOM data for two reasons. First, it is one of the two most used sites by consumers for information on cars. As mentioned by Ratchford, Lee, and Talukdar (2003), 6.59% of online automobile information searchers use the Consumer Reports website. Second, since this site only permits its' paying members to post reviews of cars, the likelihood of employees of the auto manufacturers posting reviews is reduced. As a result, the type of concerns raised by Dellarocas (2006) about online WOM data – such as hired sources of manufacturers posting overly positive reviews of their products or overly negative reviews of competitors' products – are less likely to be a problem.

Date of Rating

In addition to the rating, we collected information about the exact date of the offering of the rating. The online site Consumer Reports launched its online consumer review platform in early 2004. At the very beginning of the platform, reviewers could only offer ratings for models ranging from 2000 car models to 2004 car models, because other generations of car models, such as the 2006 Honda Accord, were not available on the US market. To illustrate the key phenomenon we mentioned previously regarding the online car rating, some reviewers offered ratings within a short duration of the purchase date, while others did so following extended use of the car. For example, one of the earliest ratings that we were able to observe and collect was for a 2004 Toyota Camry posted on March 4, 2004. The last rating for the same car model we observed was on June 22, 2008.

Reviewer's Characteristics

We also collected data on four reviewer characteristics from Consumerreports.org: Age, Gender, Driving Mileage per Year, and Driving Terrain. Table 1 reports the details of these variables.

TABLE 1
DESCRIPTIONS OF VARIABLES

Automobile Attributes	Descriptions
Design/Performance	2,2.5,3,3.5, 4,4.5, 5 and 5 means among best
Quality	2,2.5,3,3.5, 4,4.5, 5 and 5 means among best
History	Years this model name(i.e. Honda Accord) has been existed in the US market.
New	Whether the model is totally new-designed or re-designed model.
MPG	Mileage Per Gallon
Horsepower	Engine Performance
Price	Manufacturer Suggested Retail Price

Reviewer's Characteristics	Descriptions
Age	Under 30, 30-45, 46-60, over 60, and under 30 as base
Gender	Female, male, and male as base
Driving Mileage	0-10K, 10-15k, 15-20k, over 20K, and 0-10k as base
Driving Terrain	Highway, City, Mixed, and Highway as base

Key Automobile Attributes, Quality/Reliability, and Design/Performance

We collected two key automobile attribute data from J.D. Power and Associates: Quality/Reliability and Design/Performance. J.D. Power and Associates construct a quality rating ranging from 5 ("among the best") to 2 for each car model (e.g., 2006 Toyota Camry). This score looks at owner-reported problems in the first 90 days of new-vehicle ownership and is based on problems that have caused a complete breakdown or malfunction, or where controls or features may work as designed but are difficult to use or understand. We denote this variable as Quality/Reliability.

J.D. Power and Associates conducted an Automotive Performance, Execution and Layout (APEAL) study to construct a rating ranging from 5 ("among the best") to 2 for each car model (e.g., 2006 Toyota Camry). This score measures customers' perceptions of the design, features, layout, comfort, and performance of cars. We denote this variable as Design/Performance.

Other Automobile Attributes

In addition to Quality/Reliability and Design/Performance, we also collect the newness (we denote it as New) and the product life cycle stage (we denote it as History) from J.D. Power and Associates. Newness captures whether the specific model is new to the market, new to the auto manufacturer, or a re-designed or updated version of the existing model. For instance, since the Toyota Prius was first introduced to the US market in 2001, the variable New would be assigned a value of 1 for the 2001 Toyota Prius. The next time this variable takes on a value of 1 is when the redesigned 2004 Toyota Prius was introduced.

The second variable, History, measures how many years the model has been available in the US market. Some models have a very long history. The Infiniti G, for example, was introduced in 1991 and, hence, would have a 15-year history by the time the 2005 Infiniti G was launched. Honda Pilot, on the other hand, was introduced in 2003 and would only have a three-year history by the time the 2005 Honda Pilot was introduced into the US market.

Table 1 also summarizes three other automobile attributes: MPG, horsepower, and Price (manufacturer's suggested price) for each car model. Table 2 presents the summary statistics for all the variables.

TABLE 2
SUMMARY STATISTICS FOR VARIABLES

Reviewer's Charateristics	Summary	Statistics
Age	Under 30	7.37%
	30-45	39.07%
	46-60	38.25%
	Over 60	15.32%
Gender	Female	24.30%
	Male	75.70%
Driving Mileage/Year	0-10k	17.84%
	10-15k	40.11%
	15-20k	24.18%
	over 20K	17.87%
Driving Terrain	City	10.26%
	Highway	6.94%
	Mixed	82.80%

Automobile Attributes	Mean	Std. Dev.	Minimum	Maximum
Design/Performance	3.363	0.786	2	5
Quality	3.476	0.913	2	5
History	8.568	8.001	1	41
MPG	24.578	6.841	12.5	62
Horsepower	209.090	55.010	70	409
Price	27335.000	9431.000	10199	99620
New	New	27.50%		
	Not New	72.50%		

MODEL

Our dependent variable is the rating of a car model. Given the discrete and ordered nature of this variable, an appropriate model for such ordinal data is the ordered logit model. Assume that a reviewer has some level of the opinion of his or her particular car model before he/she begins to offer a rating. This opinion is represented by an unobservable variable U, where higher levels of U mean that the reviewer likes the automobile and lower levels of U mean the opposite. When offering a rating, the reviewer chooses a particular rating based on U. For instance, he/she chooses 5-"love it" if U is above some cutoff, which we label r4, or, on the other hand, he/she chooses 1-"hate it" if U is below some cutoff, which we label as r1. For our data, the choice decision is represented as

5-"Love it" if $r4<U$
4-"Pretty Good" if $r3<U<r4$
3-"OK" if $r2<U<r3$
2-"Not so hot" if $r1<U<r2$
1-"Hate it" if $U<r1$

This unobservable variable U, or reviewer's opinion, about his/her car model can be related to two groups of observable variables: an individual reviewer's characteristics and the automobile's attributes. For instance, the more a person drives the car (measured as mileage per year), the more likely it is that the car has a mechanical problem which therefore results in a negative opinion about the car. On the other hand, the lower the quality/reliability of a particular car model, the higher the likelihood of having mechanical issues which therefore results in negative opinions about the car. In addition to observable factors, other factors that affect the reviewer's opinion cannot be observed. So we can decompose U into two components:

$$U = \beta' X + \varepsilon$$

This ordinal logit model, however, ignores the fact that our data has a hierarchical structure. For instance, for the 2001 Honda Accord, there may be 100 ratings, and under the 2001 Toyota Camry, there may be 50 ratings. In the previous analysis, we pooled all reviews together and assumed that one review is independent of another. However, the real data structure suggests that ratings of the 2001 Honda Accord are similar to each other, and ratings between a 2001 Honda Accord and a 2001 Toyota Camry are less similar.

To account for the multilevel data structure, we need to modify the previous model. So, we introduce a model-specific parameter $\alpha_k$to the utility function. We assume that α_k ~N (0, σ^2) and k is the K'th car model, so:

$$U = \alpha_k + \beta' X + \varepsilon$$

Assume ε follows a logistic distribution, which means the cumulative distribution of ε is F(ε)=exp(ε)/(1+exp(ε)). So, for example,

Prob("love it")=Prob(U>r4)=Prob($\alpha_k + \beta' X + \varepsilon$ >r4)
=Prob(ε >r4-$\alpha_k - \beta' X$)=1- Prob(ε <r4-$\alpha_k - \beta' X$)
=1-(exp(r4-$\alpha_k - \beta' X$)/(1+exp(r4-$\alpha_k - \beta' X$)))
=1/(1+ exp(r4-$\alpha_k - \beta' X$))

The probabilities for the other ratings are obtained analogously. To fit the proposed model, we take a Bayesian approach to estimate β, σ^2 and the four cutoff points$\gamma s$and{α_k}. For all models, we assume diffuse priors and run a *Markov chain Monte Carlo* sampler for 5,000 iterations which serve as a burn-in period. We then obtain inferences from posterior samples from the next 25,000 iterations.

EMPIRICAL ANALYSIS

2001 Models vs. 2007 Models

As we mentioned previously, Consumer Reports launched its online consumer review platform in early 2004. We collected all consumer ratings posted between 03/04/2004 and 06/29/2008. Taking any 2001 car model, for example, we may observe some ratings posted in the middle of 2004, some between 2005, and some in the middle of 2008. Assuming that reviewers of 2001 car models bought their cars in 2001, we can infer that they used their car for at least three years to up to seven years before they offered their ratings[1]. On the other hand, ratings of 2007 models started to appear in early 2007 and continued until 06/29/2008. Therefore, we infer that reviewers of any 2007 model used their cars for at most one and half years and that many reviewers may rate their 2007 models immediately after the purchase. Therefore, this feature of our data naturally distinguishes two types of ratings: delayed ratings, as illustrated by ratings for 2001 car models (occurring long after consumers experience the car), and early ratings, as illustrated by ratings for 2007 car models (occurring soon after consumers use the car). Examining these two types of ratings separately can illustrate how the importance of Design/Performance and Quality/Reliability on the rating might change over time. As a result, we specify the utility function (1) as:

$$U = \alpha_k + \beta_1 * Design/Performance + \beta_2 * Quality + \beta_{3-7} * OtherAttributes + \beta_{8-16} * Characteristics + \varepsilon \quad (1)$$

We then fit the ordinal logit models, one for 2001 cars' ratings and one for 2007 cars' ratings. The parameter estimates are presented in Table 3. As expected, we find that the rating of a 2001 car model is positively related to the car's Quality/Reliability, but not related to its Design/Performance. On the contrary, the rating of a 2007 car model is positively associated with its Design/Performance, not its Quality/Reliability. This indicates that Design/Performance has a greater impact on the type of online opinions that occur immediately after the purchase, whereas Quality/Reliability becomes more important in the type of online opinions that occur long after the purchase.

TABLE 3
MODEL ESTIMATES FOR 2001 CAR MODELS AND 2007 CAR MODELS

	2001		2007	
	Mean	Std. Dev.	Mean	Std. Dev.
Design/Performance	0.284	0.288	**0.528**	0.218
Quality	**0.736**	0.233	0.024	0.186
History	0.002	0.239	-0.262	0.199
New	0.117	0.263	0.206	0.174
MPG	0.202	0.281	-0.068	0.284
Horsepower	0.356	0.425	0.238	0.364
Price	-0.457	0.288	-0.469	0.283
Age 30-45	**0.594**	0.216	-0.139	0.206
Age 45-60	**0.982**	0.221	-0.059	0.207
Age Over 60	**1.358**	0.237	0.244	0.254
Female	0.088	0.112	-0.193	0.146
Miles 10-15k	-0.063	0.152	-0.160	0.167
Miles 15-20k	-0.007	0.171	-0.145	0.182
Miles over 20K	0.111	0.175	-0.245	0.209
Terrain City	0.176	0.243	-0.019	0.269
Terrain Mixed	**0.457**	0.186	**0.582**	0.216
r1	**-3.381**	0.161	**-3.686**	0.164
r2	**-2.171**	0.121	**-2.672**	0.117
r3	**-1.404**	0.108	**-2.094**	0.101
r4	**0.277**	0.097	**-0.911**	0.082
σ^2	**0.585**	0.149	**0.231**	0.089
N	1969		1937	
DIC	3871		2878	
Holdout Hit Rate	50.80%		70.43%	

Note: (a) **bold** indicates significant at the 0.05 level. Same specifications are applied for Table 4 and 5; (b) DIC is deviance information criterion.

Another noticeable difference is that age has a positive effect on the 2001 rating, but not on the 2007 rating. Therefore, this analysis seems to support our hypothesis. However, one might argue that we are comparing two groups of reviewers (reviewers of 2001 car models vs. reviewers of 2007 car models) who rated two groups of different car models. This indeed is the case, because many manufacturers introduced new model names that did not exist in the market in 2001. A close look at all 201 model names examined in this analysis reveals that only 51 car models, or 25%, have both a 2001 version and a 2007 version. This means that the differences in parameters that we report may be due to the differences existing among car models and not due to when consumers provided the ratings. Nonetheless, as mentioned in Section 3, since we collected the date of each rating, we can use it to capture the effect of the timing of the rating effect. This is described in detail in Section 5.2.

Using Date of Rating

Considering 2005 models, automobile manufacturers usually released them between late 2004 and early 2005. Similarly, automobile manufacturers released 2006 models between late 2005 and early 2006. Once the 2005 models appeared on the market, consumers could purchase them during any month in 2005. Ideally, if we know that consumer A bought her/his 2005 model on May 1, 2005, and offered a rating of her/his car on June 1, 2005, we know that she/he used her/his car for exactly 30 days before offering the rating. Now assuming that another consumer B bought his/her 2005 model on May 1, 2005, as well, but offered the rating on May 1, 2007, thus we know that he/she used his/her car for exactly 730 days before offering the rating. However, our data does not contain the date for when the reviewer bought the car. We can, however, calculate the interval between the release of the car model and the date of the rating and take this as a proxy of the interval between the date of purchase and the date of the rating. Thus, for consumer A, this interval is the difference between January 1, 2005, and June 1, 2005, which is 153 days. For consumer B, this interval is the difference between January 1, 2005, and May 1, 2007, which is 852 days. An alternative option is to randomly select the date in 2005 as the date when consumer B bought his/her car and then calculate the difference of days between this date selected and May 1, 2007. We ran this simulation for all reviewers and we found that the first approach of taking the difference between the release date and the date of ratings and the second approach of the simulation produced very similar results. Therefore, in this paper, we only used the first approach and reported the results from this approach.

The final dataset included a total of 21328 ratings for 1008 car models, ranging from 2001 car models to 2008 car models[2]. We excluded the observations that missed either a reviewer's characteristics or automobile attributes. We added one new variable to our dataset named TIME, the interval between the date of releasing the car model and the date of offering the rating for the car model. As shown in Figure 1, the average rating gradually declines as the intervals go from one year to eight years. We modified the utility function (1). The new utility function (2) can be presented as the following:

$$U = \alpha_k + \beta_1 * Design/Performance + \beta_2 * Quality + \beta_3 * Time + \beta_4 * (Design/Performance * Time) + \beta_5 * (Quality * Time) + \beta_{6-10} * OtherAttributes + \beta_{11-19} * Characteristics + \varepsilon \quad (2)$$

Compared to utility function (1), in addition to Quality/Reliability and Design/Performance, we included three more variables in the current model: Time, an interaction term between Design/Performance and Time, and an interaction term between Quality/Reliability and Time. We expected both β_4 and β_5 to be significant, β_4 to have a negative sign, and β_5 to have a positive sign.

FIGURE 1
A PLOT OF AVERAGE RATING

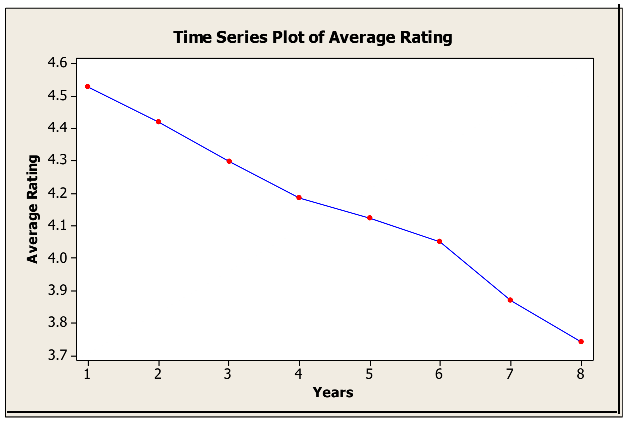

Table 4 illustrates the estimation result of this ordinal model with the interaction effects. Both coefficients of Design/Performance and Quality/Reliability were positive and significant, and in terms of the magnitude of the effects, Design/Performance was relatively larger than Quality/Reliability. As expected, there was a significant, negative interaction between Design/Performance and Time. This means that the impact of Design/Performance on online opinion decreases over time. In contrast, we obtain a significantly positive effect for the interaction between Quality/Reliability and Time. This suggests that the impact of Quality/Reliability on online opinion increases over time. Taking these two findings and the findings in Section 5.1 together, we can conclude that Design/Performance has a relatively greater effect on early online opinions; this effect decreases over time. Quality/Reliability increases its impact on online opinions over time and becomes a primary factor of delayed online opinions.

TABLE 4
MODEL ESTIMATES FOR ALL CAR MODELS

Variables	Mean	Std. Dev.
Design/Performance	**0.537**	0.073
Quality	**0.303**	0.059
Time	**-0.804**	0.045
Design/Performance*Time	**-0.280**	0.087
Quality*Time	**0.535**	0.090
History	-0.090	0.066
New	-0.091	0.065
MPG	**0.266**	0.099
Horsepower	**0.235**	0.114
Price	**-0.360**	0.081
Age 30-45	**0.129**	0.062
Age 45-60	**0.390**	0.064
Age Over 60	**0.669**	0.073

Female	-0.046	0.037
Miles 10-15k	-0.040	0.046
Miles 15-20k	-0.071	0.051
Miles over 20K	**-0.113**	0.055
City	0.146	0.075
Mixed	**0.585**	0.060
r1	**-3.871**	0.054
r2	**-2.666**	0.037
r3	**-1.967**	0.032
r4	**-0.459**	0.027
σ^2	**0.273**	0.029
N	21328	
DIC	35060	
Holdout Hit Rate	61.83%	

In addition, MPG has a significantly positive effect on online opinions, indicating that the higher the MPG of a car (thus saving money), the more favorable the online opinions towards the car. This perhaps could explain why the Chevrolet Tahoe (a fuel inefficient model) failed its online WOM campaign. Furthermore, we obtain a significantly negative sign for the coefficient of Price. This finding suggests that after we account for the other attributes (i.e., quality, design/performance, and MPG), the higher priced the car is, the less favorable the online opinion towards the car.

Turning to the reviewer's characteristics, we find that age, annual driving mileage, and driving conditions are factors that influence ratings. However, gender plays no role in the rating. More specifically, older reviewers tend to offer more favorable online opinions than younger reviewers. Reviewers who drive more, rate vehicles less favorably than reviewers who drive less. Interestingly, compared to a consumer who drives primarily on highways, consumers who drive both highway and city miles are more likely to offer positive ratings.

As discussed in Section 2, since reviewers can observe others' ratings before they offer their ratings, one may argue that the findings we have may be biased. In addition, the pattern we found may be the result of social influence, not the result of the internal evaluation through experiencing the quality or design aspect of the car. To investigate this possibility, we conducted an additional analysis including social influences.

Influences of Others' Ratings and Expert Opinions

Several studies related to online ratings illustrate that online ratings are subject to social influences. For example, Schlosser (2005) illustrates that online raters tend to adjust their evaluation after viewing others' ratings. Godes and Silva (2009) find that the trend of ratings is more negative as the volume of postings increases. Li and Hitt (2008) find that online ratings decrease over time, suggesting the self-selection of reviewers. Moon, Bergey, and Iacobucci (2010) find that online ratings of movies are significantly influenced by community-based factors, such as the average rating and rating standard deviation. Moe and Schweidel (2009) illustrate that previously posted opinions influence both actions: whether or not to offer a rating (incidence decision) and what to contribute (evaluation).

Similar to how online ratings in other categories are influenced by others' opinions, automobile consumers may also adjust their evaluations after being exposed to expert opinions. One interesting aspect of our dataset allows us to examine this effect. Recall that the website of Consumer Reports is also a third-party organization that regularly releases its expert ratings, reports, and endorsements for automobiles. We assume that each reviewer (subscribers of Consumer Reports) has a chance to be exposed to a Consumer Reports' expert opinion about the car before offering a rating about it. Therefore, we add two variables to our model: CRGood, which stands for a "Good Bet" rating for a car model by Consumer Reports that indicates a positive opinion; and CRBad, which stands for a "Bad Bet" rating for a car model by Consumer Reports that indicates a negative opinion. We expect that a positive expert opinion helps the rating, whereas a negative expert opinion hurts the rating.

In addition, we developed alternative measures to capture the influence of others' opinions: 1) the average of all previous ratings; 2) the variance of all previous ratings; 3) the volume of all previous ratings; 4) the percentage of all positive ratings (ratings of 5); 5) the percentage of all previous negative ratings (ratings of 1 or 2)[3]. Following Moe and Trusov (2009), we included the volume, average, and variance in the utility function. Utility function (3) can be specified as follows:

$$U = \alpha_k + \beta_1 * Design/Performance + \beta_2 * Quality + \beta_3 * Time + \beta_4 * (Design/Performance * Time) + \beta_5 * (Quality * Time) + \beta_{6-10} * OtherAttributes + \beta_{11-19} * Characteristics + \beta_{20} * CRGood + \beta_{21} * CRBad + \beta_{22} * Volume + \beta_{23} * Mean + \beta_{24} * Variance + \varepsilon \quad (3)$$

As reported by Moon, Bergey, and Iacobucci (2010), reviewers may pay more attention to extreme opinions and, thus, may be affected by the appearance of negative and positive opinions. We, therefore, include the volume, percentage of positive ratings, and percentage of negative ratings in the utility function. The utility function (4) can now be specified as:

$$U = \alpha_k + \beta_1 * Design/Performance + \beta_2 * Quality + \beta_3 * Time + \beta_4 * (Design/Performance * Time) + \beta_5 * (Quality * Time) + \beta_{6-10} * OtherAttributes + \beta_{11-19} * Characteristics + \beta_{20} * CRGood + \beta_{21} * CRBad + \beta_{22} * Volume + \beta_{23} * Positive + \beta_{24} * Negative + \varepsilon \quad (4)$$

One may argue that reviewers do not necessarily spend time observing all the ratings expressed previously. This particularly may be the case for our data. As shown in Figure 2, reviewers at the website of Consumer Reports can only read the first five closest (in terms of date) ratings, as they have to turn to the next page to read the next five ratings. We, therefore, expect that the first observed page that contains the first five closest ratings influence the reviewer's evaluation most, this effect decreases from the first rating to the fifth rating. Following Godes and Silva (2009), instead of including the rating directly, we categorized each rating as four dummy variables: the rating of 2, 3, 4, and 5. Now, the utility function (5) can be specified as:

$$U = \alpha_k + \beta_1 * Design/Performance + \beta_2 * Quality + \beta_3 * Time + \beta_4 * (Design/Performance * Time) + \beta_5 * (Quality * Time) + \beta_{6-10} * OtherAttributes + \beta_{11-19} * Characteristics + \beta_{20} * CRGood + \beta_{21} * CRBad + \beta_{22-25} * LagOneDummies2,3,4,5 + \beta_{26-29} * LagTwoDummies2,3,4,5 + \beta_{30-33} * LagThreeDummies2,3,4,5 + \beta_{34-37} * LagFourDummies2,3,4,5 + \beta_{38-41} * LagFiveDummies2,3,4,5 + \varepsilon \quad (5)$$

FIGURE 2
THE FIRST REVIEW PAGE OF A CAR MODEL

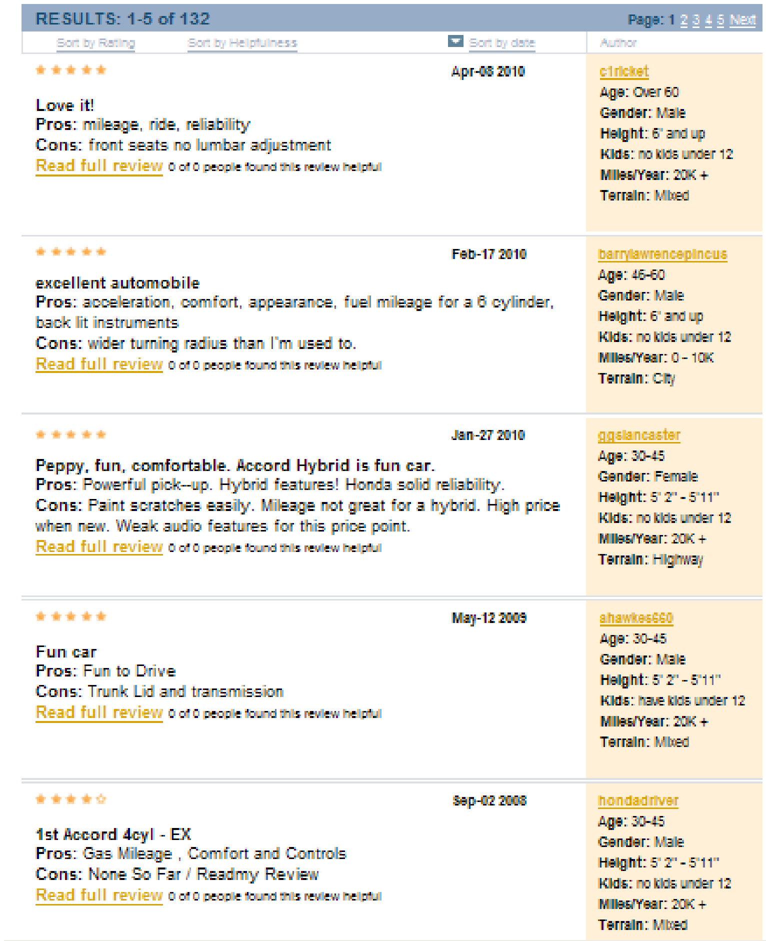

Table 5 presents the estimation results of three ordinal models with social influences. The first, second, and third models of Table 5 present results for the models with the utility functions in (3), (4), and (5), respectively. As shown in Table 5, our primary findings regarding Design/Performance, Quality/Reliability, and their interactions with Time are very similar across the three models. They are also similar to the findings from Section 5.2, where the model has no variables of social influence. Thus, both Design/Performance and Quality/Reliability have significant, positive signs. The first interaction term between Design/Performance and Time has a significantly negative sign, whereas the second interaction term between Quality/Reliability and Time has a significantly positive sign.

TABLE 5
MODEL ESTIMATES FOR ALL CAR MODELS WITH SOCIAL INFLUENCES

	Model 1			Model 2			Model 3	
Variables	Mean	Std. Dev.	Variables	Mean	Std. Dev.	Variables	Mean	Std. Dev.
Design/Performance	**0.378**	0.062		**0.362**	0.061		**0.361**	0.068
Quality	**0.162**	0.050		**0.165**	0.049		**0.214**	0.057
Time	**-0.701**	0.044		**-0.665**	0.045		**-0.691**	0.049
Design/Performance*Time	**-0.269**	0.078		**-0.277**	0.076		**-0.227**	0.087
Quality*Time	**0.473**	0.080		**0.482**	0.079		**0.450**	0.090
History	**-0.161**	0.053		**-0.157**	0.052		**-0.177**	0.061
New	-0.071	0.053		-0.073	0.051		-0.054	0.058
MPG	**0.184**	0.079		**0.171**	0.078		0.161	0.090
Horsepower	0.162	0.093		0.160	0.094		0.104	0.105
Price	**-0.235**	0.071		**-0.259**	0.070		**-0.161**	0.077
Age 30-45	**0.131**	0.064		**0.134**	0.063		0.065	0.071
Age 45-60	**0.390**	0.064		**0.396**	0.062		**0.323**	0.070
Age Over 60	**0.664**	0.072		**0.669**	0.072		**0.604**	0.082
Female	-0.055	0.037		-0.053	0.036		-0.019	0.041
Miles 10-15k	-0.045	0.047		-0.047	0.045		-0.017	0.052
Miles 15-20k	-0.069	0.052		-0.070	0.050		-0.077	0.057
Miles over 20K	**-0.108**	0.055		**-0.109**	0.054		-0.104	0.062
Terrain City	0.143	0.076		0.144	0.075		0.117	0.084
Terrain Mixed	**0.579**	0.060		**0.576**	0.059		**0.548**	0.067
CRGood	**0.287**	0.051		**0.293**	0.050		**0.275**	0.056
CRBad	**-0.406**	0.085		**-0.396**	0.080		**-0.488**	0.094
Volume	-0.067	0.047		**-0.093**	0.047	Lag 1 Rating 2	-0.025	0.126
Mean	**0.306**	0.051	Negative	**-0.095**	0.039	Lag 1 Rating 3	0.118	0.122
Variance	-0.016	0.045	Positive	**0.322**	0.049	Lag 1 Rating 4	**0.216**	0.107
						Lag 1 Rating 5	**0.317**	0.106
						Lag 2 Rating 2	-0.200	0.127
						Lag 2 Rating 3	0.022	0.124
						Lag 2 Rating 4	0.128	0.111
						Lag 2 Rating 5	**0.232**	0.109
						Lag 3 Rating 2	-0.130	0.131
						Lag 3 Rating 3	0.044	0.128
						Lag 3 Rating 4	0.074	0.114
						Lag 3 Rating 5	0.110	0.112
						Lag 4 Rating 2	0.120	0.134
						Lag 4 Rating 3	**0.258**	0.128
						Lag 4 Rating 4	0.216	0.114
						Lag 4 Rating 5	**0.283**	0.114
						Lag 5 Rating 2	-0.152	0.132
						Lag 5 Rating 3	0.082	0.129
						Lag 5 Rating 4	0.081	0.115
						Lag 5 Rating 5	0.137	0.112
r1	**-3.863**	0.052		**-3.853**	0.050		**-3.954**	0.056
r2	**-2.660**	0.034		**-2.653**	0.034		**-2.722**	0.038
r3	**-1.964**	0.028		**-1.960**	0.028		**-2.008**	0.032
r4	**-0.466**	0.022		**-0.465**	0.022		**-0.508**	0.026
σ^2	**0.117**	0.024		**0.104**	0.021		**0.132**	0.025
N	21328			21328			17824	
DIC	35090			35080			28800	
Holdout Hit Rate	61.83%			61.76%			62.55%	

However, a noticeable difference between the model without social influences and the models with social influences is the magnitude of the coefficients. The models with social influences have smaller coefficients of Design/Performance and Quality/Reliability than the model without social influences, suggesting that some effects have been explained by social influences. Overall, the results illustrate that even including various patterns of social influences, the impact of Design/Performance on online opinion decreases over time, whereas Quality/Reliability increases its impact on online opinion over time.

While the primary findings are important, the social influences on online opinion are also worthy to be discussed. First, across the three models in Table 5, we obtain a significantly positive sign for the coefficient of CRGood and a significantly negative sign for the coefficient of CRBad. This means that expert opinions do affect online opinions. A positive expert opinion of a car improves an individual's rating of the car, whereas a negative expert opinion of a car lowers an individual's rating of the car. In addition, a negative expert opinion hurts the rating more than the positive effect of a positive expert opinion. Such a negative bias has also been reported in other related studies (i.e., Basuroy, Chatterjee, and Ravid 2003; Moon, Bergey, and Iacobucci 2010).

Second, our findings across three models support the notion that previously expressed opinions influence consumers' opinions. In the first model with the volume, the average, and variance of the previous online opinions, we obtain a significant and positive relationship between the average of previous online opinions and the online opinion. This finding is intuitively meaningful because an individual reviewer's evaluation is more likely to follow a community consensus. Moon, Bergey, and Iacobucci (2010) find a similar relationship for the movie category. However, a mixed finding appears for the volume of previous opinions. Specifically, although its effect is not significant for the first model, its effect is significant and negative for the second model, where we include the volume, percentage of positive other opinions, and percentage of negative other opinions. Consistent with Godes and Silva (2009), this suggests that the online opinion becomes negative as the volume of the postings increases.

We also find that the percentage of positive opinions in the previously posted opinions increases the rating while the percentage of negative opinions decreases the rating. However, unlike the findings in Moon, Bergey, and Iacobucci (2010), which support a negative bias for the movie category, we find that positive opinions have a larger effect than negative opinions on the rating. Finally, in the third model, we find that the first closest past rating (relative to the other four past ratings) has the largest effect on the rating. This effect is generally decreasing from the first closest to the fifth closest, except for the fourth rating.

Turning to other automobile attributes, we find that History is significantly negatively related to online ratings. This means that the longer the car model has been in the market, the less favorable the opinion towards the car will be. This finding seems to be counter-intuitive at first glance, because the longer the model's history is, the larger the loyal consumer base should be, which, in turn, should improve the online opinion. However, long-standing models such as Toyota Camry and Honda Accord, are more likely to establish high expectations among their consumers, which makes them very hard to delight and excite consumers. Finally, MPG and Price are related to online opinions, which are consistent with the findings in Section 5.2.

DISCUSSION, IMPLICATIONS, AND LIMITATIONS

Discussion

This paper makes use of a unique dataset containing online opinions about automobiles, various automobile attributes, and reviewers' characteristics to study the mechanism of online opinions. We contribute to this growing literature on online WOM in two important aspects: first, to our knowledge, our study is the first attempt to examine the joint effects of two critical product attributes, Design/Performance, and Quality/Reliability, on the online opinion in a dynamic setting; second, since we view the online opinion as a different evaluation process from customer satisfaction, we model the online opinion by incorporating various social influences.

The results of our study illustrate that, depending on the timing of the online opinion, Design/Performance and Quality/Reliability play different roles. Design/Performance plays a major role in the early online opinions (occurring soon after the purchase) and this effect decreases over time, whereas Quality/Reliability increases its impact on online opinions over time and becomes a primary factor of the delayed online opinions (occurring long after the purchase). We reason that consumers typically have limited knowledge about a new car when they just purchase and experience the car. However, they may be able to quickly feel excited about the design (i.e., fancy body style, luxury interiors) and the driving performance of the car. So we expect that if consumers engage in online discussions soon after they purchase the car, their opinions are more likely to revolve around the design/performance of the car. As consumers experience the car for a longer time, they have more opportunities to experience problems related to the quality (i.e., engine or transmission failures, and other mechanical issues). They are thus able to evaluate the car based more on the quality. In addition, consumers' initial excitement toward the design/performance of the car may dilute over time. Therefore, we reason that if consumers discuss the car after using it for a longer period, their evaluations are more likely to be related to the quality of the car.

As we emphasized throughout the paper, on the one hand, online opinions share similarities with customer satisfaction. Our primary finding is in line with the experimental finding on satisfaction from Homburg, Koschate, and Hoyer (2006): the influence of the effect on the satisfaction decreases over time and the impact of cognition on satisfaction increases over time. On the other hand, an opinion is not similar to satisfaction. Online opinions are subject to social influences. We thus incorporate various social influences in the model and find that the opinions expressed previously affect consumer ratings. More specifically, an individual reviewer tends to follow the community consensus: a higher percentage of positives in the previously expressed opinions improves consumer ratings while a larger percentage of negatives worsens the same. In addition, we also find that positive expert opinions improve ratings while negative expert opinions hurt them. Further, the negative effect of negative expert opinions is larger than the positive effect of positive expert opinions.

Implications

Several implications follow from our study. First, we illustrate that it is important to view and examine online WOM from a dynamic perspective. Online opinions towards the same product can occur from the first moment of introducing a product and continue over a period of several years after the introduction. Moreover, many online WOM communities (i.e., review sites) maintain all ratings which mean that this characteristic of persistence enables people to observe the entire history of online conversations over time about the same product.

Most importantly, the online WOM activities that occur soon after the introduction of the product, or the early online WOM defined in this paper, play a vital role in establishing product awareness and increasing sales. It is perhaps for this reason that many firms are interested in simulating positive consumer opinions during the beginning of a product's life cycle under the assumption that the early WOM spreads the information about the product and functions as a promotional tool to stimulate sales. Although the delayed online WOM activities can also help firms in other ways (i.e., creating brand loyalty), creating an early WOM seems to be the optimal strategy for many firms.

Second, we investigate the roles of two critical product attributes, Design/Performance, and Quality/Reliability, in the online opinion. Intuitively, one would expect both attributes to be important factors of this evaluation process, because the fancy design of the car excites consumers and the high quality of the car satisfies consumers. As a result, both should contribute to the positive side of this evaluation. However, we illustrate that when considering the timing of this evaluation process, Design/Performance and Quality/Reliability play different roles. Design/Performance plays a major role in the early online opinions and Quality/Reliability becomes a main factor in the delayed online opinions. This finding implies that a firm should focus on improving the Design/Performance of the product if its primary goal is to create positive word of mouth very early in the life cycle. On the other hand, if a firm's goal is to take advantage of positive online WOM in the long run, the focus has to be on improving the quality/reliability of the product.

Because of budgets, many firms, especially automobile manufacturers, are often forced to trade-off between Design/Performance and Quality/Reliability. Without the constraint of the budget, the best solution is to improve both the Design/Performance and Quality/Reliability, thus maximizing both types of WOM. However, more often than not, firms are forced to focus on either Design/Performance or

Quality/Reliability for various reasons. In such situations, we suggest that for those firms that are only interested in creating consumer discussions in the early stages of a product's life cycle, the best strategy is to improve upon the Design/Performance of the product.

Third, since we examined online opinions on automobiles, we believe that the results of this study provide valuable implications for automobile manufacturers. Automobile manufacturers are interested in stimulating consumer conversations for newly released models. Several auto brands (i.e., Scion, Ford, and Chevrolet) invite consumers to talk about their models to others in the hope that such conversations can generate awareness, as well as sales. If a manufacturer has multiple new models, since not all models can be promoted effectively through consumer word of mouth, one or a few models have to be chosen as candidates for stimulating consumer conversations. Based on this study, we suggest that a better-designed model with high MPG and a relatively low price be the top choice in such cases. We expect that positive online opinions would be created in the early stages and can thus function as promotional tools to create both awareness and sales. The practices of the automobile industry seem to support our suggestion. For example, both Scion xB and Ford Fiesta successfully utilized viral marketing campaigns to generate high sales. Both models fit into the category we suggested: better designed high MPG and low prices. On the contrary, Chevrolet Tahoe, a utility model with low MPG and a relatively high price, failed in such a campaign.

Finally, our findings on social influences on online opinion suggest that automobile marketers may use various social influences to improve online opinion. First, since positive expert opinions help online opinion, marketers should expose good news to both potential customers and current customers. Advertising such expert endorsements (i.e., a J.D. Power Associates award) may help to improve online opinions. Second, automobile marketers should encourage their delighted/satisfied customers to contribute their positive experiences online. The rationale is that a more positive community environment (i.e., a high percentage of positive opinion) may motivate the online opinion positive.

Limitations and Future Study

We indicate some limitations of this study and shed light on potential avenues for further research. First, as mentioned previously, we have the date of offering the rating for the car, but we do not have the date of the purchase of the car. We, therefore, calculated the interval between the date of the release of the car model and the date of the rating and took this as a proxy of the interval between the date of purchase and the date of the rating. We also did simulations of the date of the purchase of the car and took the interval between this date and the date of the rating. We found that the relationship between the two intervals is linear. Because of the linear relationship between the two intervals, the estimated coefficients in our specifications and their standard errors would simply be scaled by a constant. Nevertheless, if the data for the date of the purchase is available, it is worthwhile to validate our results. Alternatively, one could turn to an MSN auto review site, which provides the categorical data of ownership, such as "less than one year or two years".

Second, we do not account for consumer heterogeneity across reviewers. In our data, the majority of reviewers only offer a single rating for one car. If, however, we have data in which each reviewer has multiple ratings for multiple cars, we would be able to obtain reviewer-specific parameters. Such reviewer-level analyses can provide richer insights than cross-sectional models as in our case here.

Third, our empirical analysis is limited to a single category. While this category is important in terms of its size in the economy, and the number and variety of competitors, it is important to replicate our findings in other product categories to assess the generalizability of our theory across multiple categories.

Finally, we only analyzed online WOM data from the Consumer Reports website. Therefore, sampling bias could be an issue. One solution could be to collect online WOM data from several other automobile websites (i.e., Yahoo, MSN, or Edmunds).

ENDNOTES

1. It is possible that some reviewers may buy used cars and own them for a short time before posting reviews. However, when these consumers evaluate the cars, they would take the past ownership into a consideration.
2. We excluded 2000 car models, because we didn't have automobile attribute variables for them.
3. We used the number of reviews rating a model year as a 5 ("love it") as the measure of positive WOM and the number of reviews giving a rating of a 2 ("not so hot") or 1 ("hate it") as the measure of the negative WOM. We are more conservative in the designation of a review as positive because empirical evidence (Chevalier and Mayzlin 2006) suggests that consumer reviews tend to be overwhelmingly positive. We, therefore, designate a review as positive only if the reviewer gives the highest possible rating to a car. On the other hand, ratings that are extremely negative (for example, a rating of 1), or close to being extremely negative (e.g., a rating of 2), are designated as negative since there is little empirical evidence of consumers being overly negative. Hence, extremely negative, or close to being so, are both designated as negative ratings.

REFERENCES

Armstrong, G., & Kotler, P. (2009). *Marketing An Introduction* (9e). Upper Saddle River, NJ: Pearson Prentice Hall.

Basuroy, S., Chatterjee, S., & Ravid, A. (2003). How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets. *Journal of Marketing*, *67*(October), 103–117.

Chen, Y., & Xie, J. (2008). Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix. *Management Science*, *54*(3), 477–491.

Chevalier, J., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, *43*(3), 345–354.

Clemons, E.K., Gao, G., & Hitt, L.M. (2006). When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry. *Journal of Management Information Systems*, *23*(2), 149–171.

Comscore. (2007). *Online Consumer-Generated Reviews Have Significant Impact on Offline Purchase Behavior*. Press Release.

Dellarocas, C. (2006). Strategic Manipulation of Internet Opinion Forums: Implications for Consumers and Firms. *Management Science*, *52*(10), 1577–1593.

Dellarocas, C., & Narayan, R. (2006). A Statistical Measure of a Population's Propensity to Engage in Post-Purchase Online Word of Mouth. *Statistical Science*, *21*(2), 277–285.

Dellarocas, C., & Narayan, R. (2007). *Tall Heads vs. Long tails: Do Consumer reviewers increase the informational inequality between hit and niche products?* Working paper.

Dellarocas, C., Zhang, X., & Awad, N.F. (2008). Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures. *Journal of Interactive Marketing*, forthcoming.

Dellarocas, C.N. (2003). The Digitization of Word-of-Mouth: Promise and Challenges of Online Feedback Mechanisms. *Management Science*, *49*(10), 1407–1424.

Duan, W., Gu, B., & Whinston, A.B. (2008). Do Online Reviews Matter? – An Empirical Investigation of Panel Data. *Journal of Retailing*, forthcoming.

Eliashberg, J., & Shugan, S.M. (1997). Film Critics: Influencers or Predictors? *Journal of Marketing*, *61*(April), 68–78.

Forbes. (2007). *Will Scion Change the World?*

Forbes. (2009). *Ford Taps Web-Savvy Hipsters to Hype Fiesta.*

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

Godes, D., & Mayzlin, D. (2009). Firm-Created Word-of-Mouth Communication: Evidence from a Field Study. *Marketing Science*, *28*(4), 721–739.

Godes, D., & Silva, J. (2009). *The Dynamics of Online Opinion*. Working Paper.

Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeffer, B., . . . Verlegh, P. (2005). The Firm's Management of Social Interactions. *Marketing Letters*, *6*(3/4), 415–28.

Hennig-Thurau, T., Gwinner, K.P., Walsh, G., & Gremler, D.D. (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.
Li, X., & Hitt, L.M. (2008). Self-Selection and Information Role of Online Product Reviews. *Information Systems Research*, *19*(4), forthcoming.
Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*, *70*, 74–89.
Mayzlin, D. (2006). Promotional chat on the internet. *Marketing Science*, *25*(2), 155–163.
Moe, W., & Schweidel, D. (2009). *Online Product Opinion: Incidence, Evaluation and Evolution*. Working Paper.
Moe, W., & Trusov, M. (2010). *Measuring the Value of Social Dynamics in Online Product Ratings Forums.* Working Paper.
Moon, S., Bergey, P.K., & Iacobucci, D. (2010). Dynamic Effects among Movie Ratings, Movie Revenues, and Viewer Satisfaction. *Journal of Marketing*, *74*, Forthcoming.
Opinion Research Corporation. (2009). *Online Feedback Significantly Influences Consumer Purchasing Decisions.*
Ratchford, B., Lee, M-S., & Talukdar, D. (2003). The Impact of The Internet on Information Search for Automobiles. *Journal of Marketing Research*, *40*(2), 193–209.
Schlosser, A. (2005). Posting Versus Lurking: Communicating in a Multiple Audience Context. *Journal of Consumer Research*, *32*, 260–265.
Srinivasan, S., Pauwels, K., Silva-Risso, J., & Hanssens, D.M. (2009). Product Innovations, Advertising, and Stock Returns. *Journal of Marketing*, *73*(1), 24–43.