# THE IMPACTS OF ELECTRONIC WORD-OF-MOUTH ON HIGH-INVOLVEMENT PRODUCT SALES: MODERATING EFFECTS OF PRICE, BRAND ORIGIN, AND NUMBER OF CUSTOMERS

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## ABSTRACT

Electronic word-of-mouth (eWOM) has become an invaluable information source for consumers to make purchase decisions and is highly valued by companies. Extensive studies have explored how eWOM affects sales; however, the results are inconsistent. To reconcile these mixed findings, we leverage signaling theory. From the signaling perspective, product signals may attenuate or strengthen the influence of eWOM on product sales. Focusing on the automotive industry, a typical domain of high-involvement products, we investigate the moderating effects of three critical product signals (i.e., price, brand origin, and the number of customers) on the relationship between eWOM and car sales using a panel dataset collected from a leading eWOM platform. The results show that the awareness effect of eWOM on high-involvement product sales is more influential when (1) the product price is lower, (2) the product has a larger number of customers, and (3) the product belongs to foreign brands. These findings contribute to the literature and help business practitioners better understand the impact of eWOM on sales in the context of high-involvement products.

Keywords: Electronic word-of-mouth; Price; Brand origin; Number of customers; Car sales

## 1. Introduction

In recent decades, the internet has profoundly changed the way in which information is transmitted. With the help

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of the internet, consumers can share their experiences and opinions with millions of internet users by posting online reviews after consumption (Cheung & Lee, 2012; Maslowska et al., 2017). Electronic word-of-mouth (eWOM) refers to these reviews, comments, and opinions. According to a report by Bright Local, 86% of consumers read online reviews before making purchase decisions (Murphy, 2018). Accordingly, eWOM has been recognized as a positive and effective marketing tool through which to execute business strategies (Dellarocas, 2003). Business, for instance, utilize consumer reviews to determine product pricing power (Archak et al., 2011), encourage consumers to share eWOM about their products (Godes & Mayzlin, 2004), and even manipulate eWOM strategically to influence potential buyers' purchase decisions (Dellarocas, 2006).

The underlying belief behind such strategies is that eWOM can significantly influence potential consumers' purchasing decisions. Previous studies offer extensive evidence that eWOM has a significant effect on product sales (Archak et al., 2011; Chevalier & Mayzlin, 2006; Chintagunta et al., 2010; Clemons et al., 2006; Gopinath et al., 2014; Kim et al., 2019; Li et al., 2019; Maslowska et al., 2016; Qin, 2011). However, another challenging reference group suggests the opposite (Amblee & Bui, 2011; Duan et al., 2008a; Forman et al., 2008; Liu, 2006; Park et al., 2012) In the absence of systematic insight, marketers are unable to make informed decisions about eWOM management (Rosario et al., 2016).

The above disagreement is probably due to the different research contexts in the field of eWOM. A meta-analytic review conducted by Rosario et al. (2016) concludes that the effect of eWOM varies across platforms, products, and metrics. Few studies examine how product popularity (Zhu & Zhang, 2010), product characteristics (Lee et al., 2011; Lu et al., 2014; Maslowska et al., 2017; Wang et al., 2015; Zhang et al., 2019), and user characteristics (Zhu & Zhang, 2010) interact with eWOM in the purchase decision process. Therefore, contextual factors which may influence the effects of eWOM on product sales should be further investigated.

Due to information asymmetry, consumers are used to searching and reading eWOM to reduce uncertainty; meanwhile, marketers tend to send positive product signals to potential consumers and induce consumption. Therefore, consumers are faced with eWOM generated by peers and product signals provided by marketers before making decisions. Consumers are likely to utilize eWOM to varying extents depending on the helpfulness/usefulness of the product signals. According to signaling theory, signals are visible cues that can infer the quality of a product/service, which is generally difficult to evaluate due to information asymmetries (Spence, 1978). Quality signals can be transmitted in many channels, including the brand, price, warranty, advertising, certificates, etc. In this study, we focus on three common product signals (i.e., price, brand origin, and the number of customers) and examine how these signals attenuate or strengthen the influence of eWOM on product sales.

The automotive industry, a specific domain of high-involvement products, provides an ideal research context for this study to explore the interactions between product signals and eWOM. Involvement refers to the extent to which consumers are interested in and engaged with a product (Richins & Bloch, 1986). It reflects the importance that consumers attach to a specific product and affects consumer behavior. Research has shown that extensive information search and complicated decision-making are required before purchasing high-involvement products (Hoyer et al., 2008). Cars are usually expensive, complex, and durable products. Hence, for most consumers, buying cars is a substantial financial expense and an information-intensive decision. Thus, eWOM should play an essential role in this process. Moreover, the automotive industry's vast marketing budget and its importance to economic development make it an exciting test-bed with critical practical implications (Geva et al., 2017).

The empirical results of this study confirm the positive effect of eWOM volume on sales in the context of high-involvement products and demonstrate that foreign brands and the number of customers amplify this positive effect, whereas prices weaken this positive effect. This study fills the gap in the extant literature by examining the joint effect of eWOM and product signals and helps to understand the underlying mechanism of eWOM on consumer behavior. Our findings also provide practical suggestions for consumers to make optimal purchase decisions and offer managerial implications for firms regarding the management of eWOM and product marketing.

The remainder of this paper proceeds as follows. We first deduce our hypotheses based on a related literature review in Section 2. Section 3 presents the data collection process, definitions of the main variables, and model specification. Then, we describe our dataset and report the primary analysis results in Section 4. Robustness checks are conducted in Section 4. Finally, we summarize the findings and discuss their contributions in Section 5 and Section 6, respectively.

## 2. Literature Review and Hypothesis Development

### 2.1 Signaling Theory

In this study, we attempt to understand whether price, brand origin and the number of customers strengthen or attenuate the impact of eWOM on sales in the context of high-involvement products. To answer this question, we leverage signaling theory. Signaling theory is fundamentally concerned with reducing information asymmetry between two parties (Spence, 2002). Typically, one party, the signaler, must choose whether and how to communicate (or signal) that information, and the other party, the receiver, must choose how to interpret the signal (Connelly et al., 2011). The signaling theory suggests that signals are observable alterable attributes that individuals and organizations can use to communicate (Spence, 1973), and quality refers to the underlying, unobservable ability of the signaler to fulfill the needs or demands of receivers observing the signal(Connelly et al., 2011). The signaling theory has been applied to help explain the influence of information asymmetry in a wide array of research contexts, such as corporate governance (Miller & Triana, 2009; Zhang & Wiersema, 2009), human resource management (Fu et al., 2021) and financial markets (Bhattacharya, 1979; Ross, 1973).

Based on signaling theory, Kirmani and Rao (2018) discuss buyers' uncertainty about product quality and develop a typology of marketing signals in the framework of consumer decision-making. With regard to a specific transaction, different parties may hold various information, which leads to information asymmetry. The manufacturer or service provider has complete information on the quality of the product. In order to facilitate the transaction, manufacturers or service providers have an incentive to strategically provide product quality information to potential consumers and users, including prices and brand information, etc. On the other hand, potential consumers collect product information to reduce uncertainty and purchase risk.

The signaling theory is particularly useful in the context of high-involvement products, where customers usually face higher product uncertainty and perceived risk. For high-involvement products such as automobiles, which are complex, expensive, and durable products, potential customers often spend considerable time searching for product information to engage in a more comprehensive evaluation of the various alternatives(Clarke & Belk, 1978) because incorrect purchase decisions have serious financial implications and force consumers to deal with poor products for long periods of time (Laurent & Kapferer, 1985). Traditional product quality signals provided by manufacturers or service suppliers may be manipulated (Blazevic et al., 2013; Liu, 2006). EWOM, which is a statement generated by customers about a specific product or service and is accessible to a multitude of people via the internet, therefore serves as supplemented product quality signals to subsequent consumers (Hennig-Thurau et al., 2004). Potential consumers can infer the unobservable quality of products from these user-generated signals by social learning (Huang et al., 2019).

However, thus far as we know, limited scholarly attention is devoted to how consumers meaningfully aggregate the two types of signals when making purchase decisions. Most of the extant related studies are conducted in the travel and tourism field. For example, Kim (2021) finds that consumers tend to rely less on online review valence if the sellers signal positive product quality with verifiable information cues. Wang et al. (2015) and Lu et al. (2014) find similar results. Lu et al. (2014) show that both the average rating of online WOM and rating variance have more impact on sales for hotels with lower rather than higher star ratings. Wang et al. (2015) find that if hotels receive positive WOM, their online sales performance is less likely to be influenced by room price and star rating. In the video game industry, Zhu and Zhang (2010) indicate that online reviews are more influential for less popular games. Kostyra et al. (2016) find that eWOM reduces the influence of brand and price on customers' choices in their choice-based conjoint experiment about eBook readers. These studies verify that the effects of eWOM are moderated by traditional product signals.

Unlike prior literature, this study assesses the moderating role of price, brand origin and the number of users in the relationship between eWOM volume and product sales in the context of the Chinese automotive industry. In the automotive industry, price and brand are undoubtedly very important quality signals for potential car buyers. In addition, the total number of users is also an important signal. According to network effects (Katz & Shapiro, 1994), more users mean more convenient after-sales service and lower maintenance costs. Finally, in this study, we focus on the volume rather than the valence of eWOM because customers usually conduct many information searches and product comparisons before making purchase decisions for high-involvement products. They are usually satisfied with the products, and their eWOM ratings are usually relatively high. For example, the average score of all eWOM ratings is as high as 4.2 (log value is 1.43) in our data.

### 2.2 eWOM Volume

The eWOM volume is the number of online reviews or comments for a particular product. The previous literature presents mixed findings concerning eWOM volume. While some studies demonstrated a positive effect of eWOM volume on sales (Gopinath et al., 2014; Gu et al., 2012; Sun, 2012), others found no evidence supporting this conclusion (Chintagunta et al., 2010; Moe & Trusov, 2011). A further study conducted Ho-Dac et al. (2013) suggests that the effect of eWOM volume on sales varies by product type.

As a typical high-involvement product, automobiles are characterized by complex functionality, high price, and long life. As such, consumers are more engaged in the purchase decisions of these products. Due to information asymmetry, consumers are more likely to obtain product information from multiple sources, especially external WOM sites that provide access to information such as user experience, quality, and performance (Gu et al., 2012). In the automobile industry, eWOM platforms are established by third parties, which makes eWOM relatively more reliable.

In the context of high-involvement products, a larger volume of eWOM indicates more information, which is helpful in reducing uncertainty due to information asymmetry and encouraging purchases (Filieri et al., 2020). Meanwhile, eWOM volume can be viewed as a proxy of popularity (Filieri et al., 2018). The extant literature provides significant evidence that consumers tend to follow others' choices, which is known as herding (Decker & Trusov, 2010). Therefore, the pivotal role of eWOM volume in consumers' purchase decisions is evident (Geva et al., 2017; Gu et al., 2012; Netzer et al., 2012; Wang et al., 2021). We thus propose the following hypothesis.

*H1: The volume of electronic word-of-mouth regarding a car is positively associated with its sales.*

### 2.3 Product Price

While eWOM has become a very important information source for consumers (Cui et al., 2012; Zhu & Zhang, 2010), additional analysis demonstrates that consumers also actively search for external information, such as prices, to reduce the perceived risk before purchasing high-involvement products (Gu et al., 2012).

Product price is a crucial product signal that consumers consider when making decisions. The effect of eWOM may vary based on the price of the product. Guadalupi (2018) found that product prices not only provide information about goods but also affect information dissemination and information exposure. On the one hand, the price of automobiles delivers a vital quality signal of products and determines customers' expectations of a product (Mitra & Fay, 2010; Peterson, 1970). One of the most common market beliefs is that one can infer the quality of a product by its price (Solomon, 2011). Specifically, automobiles with higher prices are certified to be of high quality, as manufacturers invest more in R&D, design, branding, marketing, and after-sales services. A higher price guarantees product quality and relieves customers' concerns. Potential customers, therefore, depend less on alternative user-generated signals of product quality. In contrast, automobiles with lower prices suffer higher uncertainty in quality. Customers, consequently, rely more on alternative cues, such as user-generated quality signals.

On the other hand, Milgrom and Roberts (1986) suggest that lower prices are effective in delivering quality information, especially when high-quality producers are more efficient. As the majority of consumers are rational, their purchase decisions are restricted to budget constraints. Higher prices create a threshold for potential customers and decrease the number of individuals who can afford them. Accordingly, low prices increase the exposure of eWOM and amplify the effect of eWOM volume, whereas high prices impede the dissemination and exposure of eWOM and hence impair the effect of eWOM on sales (Guadalupi, 2018). Thus, we propose the following hypothesis.

*H2: Low price enhances the relationship between the volume of electronic word-of-mouth and car sales.*

### 2.4 Number of Customers

The number of customers of a product reflects its popularity or market share, which is another important cue of product quality in marketing (Jang & Chung, 2021) and affects consumers' decision-making in several ways (Sunder et al., 2019). On the one hand, the number of customers captures the preference of collective consumers (Decker & Trusov, 2010). The market tends to present the phenomenon that "the winner takes all" because of herding behavior (Wang et al., 2019). The eWOM of automobiles with a larger number of existing users is consequently more likely to attract the attention of potential consumers.

On the other hand, the existing users of a model of cars will construct an invisible network. Larger networks with more users will have a stronger demand-side economy of scale effect than smaller networks with fewer users. The value of networks will increase exponentially as the total number of users increases based on the theory of the network effect (Katz & Shapiro, 1994). The network effect arouses consumers' interest in the product and leads to consumers' information searching (Aguilar et al., 2020). User network effects will consequently enhance the influence of eWOM on purchasing decisions in cars with a larger number of existing users.

In short, consumers probably conduct extensive information searching of both traditional quality signals (e.g., the number of users) and user-generated quality signals (e.g., eWOM) in the consideration and preference stages of purchase decisions in the context of high-involvement products. Due to consumer conformity, the number of existing users arouses potential consumer interest in specific automobiles, promoting the effort that consumers make to learn supplementary knowledge from eWOM. Therefore, we speculate that the number of existing users may magnify the effects of eWOM volume on car sales. Thus, we propose the following hypothesis.

*H3: The number of users enhances the relationship between the volume of electronic word-of-mouth and car sales.*

### 2.5 Brand Origin

Brand origin or country of origin is also an important product signal (Solomon, 2011). First, the brand origin of a product is critical to consumers' choice (Magnusson et al., 2011; Usunier, 2011), and previous research stressed the strong quality signal of brands (Erdem & Swait, 1998). According to Batra et al. (2000) and Zhou et al. (2010), nonlocal brands are more popular among consumers in emerging economies than domestic brands due to their perceived quality and social status. Specifically, this type of preference or bias is more salient for high-involvement goods, such as automobiles, because foreign brand automobiles are usually labeled with a higher-quality, advanced technology and better design than local brands in emerging economies (Wang & Yang, 2008). The preference for foreign brands may appeal to consumers at the awareness stage and facilitate the complementary information search at the consideration stage, e.g., social learning from peers' comments (Huang et al., 2019). Therefore, consumers tend to exert more effort in drawing helpful information from user-generated signals of products when evaluating foreign brand cars and consequently magnify the effect of eWOM on car sales.

Second, the nature of foreign brands rooted in different cultures may cause cross-cultural conflict effects in product evaluation. Traditional quality signals have limited ability to explain the uncertainty introduced by these differences. Therefore, consumers need to learn more about the product through complementary cues of product performance prior to making choices among foreign automobiles. eWOM, which involves indirect experience from peers, has a more prominent voice in this case.

In a word, consumers are more dependent on the helpful signals of specific products embedded in user-generated signals when evaluating foreign brand cars. Therefore, we propose the following hypothesis.

*H4: Compared with local car brands, the volume of electronic word-of-mouth has a stronger impact on the sales of foreign car brands.*

We summarize the framework of this research in Figure 1.

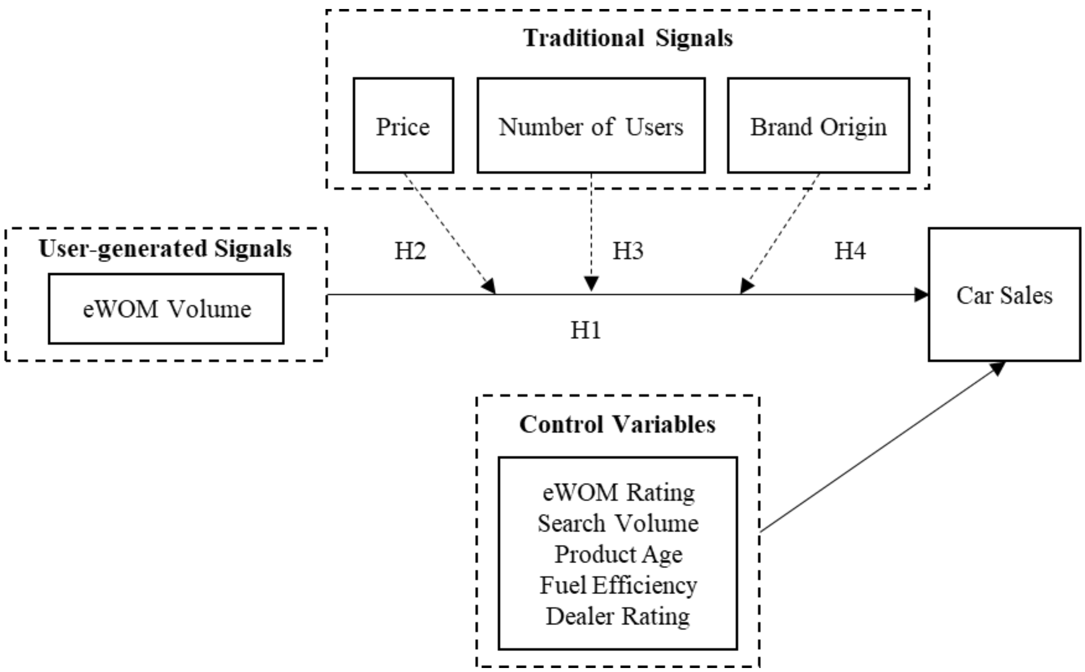


Figure 1: Summary of the Research Model

## 3. Methodology

### 3.1 Data

We build a panel dataset of eWOM, the search volume index, and sales information. These data are obtained from Autohome, Baidu, and CSMAR. The eWOM data are collected from Autohome, a leading online destination for Chinese automobile consumers. Our dataset includes over 1 million online reviews of almost all car models in the Chinese automobile market from September 2012 to July 2019. The eWOM rating system on Autohome is a multidimensional rating system that includes ratings of the space, engine, handling, comfort, fuel efficiency, exterior, interior, and cost performance of a given car. To facilitate a horizontal comparison among various car models, Autohome provides an overall rating of each car model, which is the average value of multidimensional ratings from all the reviews of a car model. In addition to the numeric ratings, the eWOM data include the car model, city, dealer, rating of the dealer, purchase date, the actual purchase price (tax excluded), real fuel efficiency (l/100 km), mileage (km), usage purpose, photos, and review texts. Figure 2 shows an example of a consumer review of the Toyota RAV4 from Autohome, and Figure 3 presents the overall rating and number of reviews for Toyota the RAV4.

The search volume index of each car model is collected from Baidu, which is the most popular search engine in China. Baidu provides a weighted search volume index, i.e., the Baidu Search Index (BSI) (http://index.baidu.com), which is accessible to the public. We carefully selected the search terms to avoid ambiguity before collecting the Baidu search volume index. By default, the search terms are car model names. Additionally, the brand name is added in front of the car model name as a search keyword to avoid ambiguity.

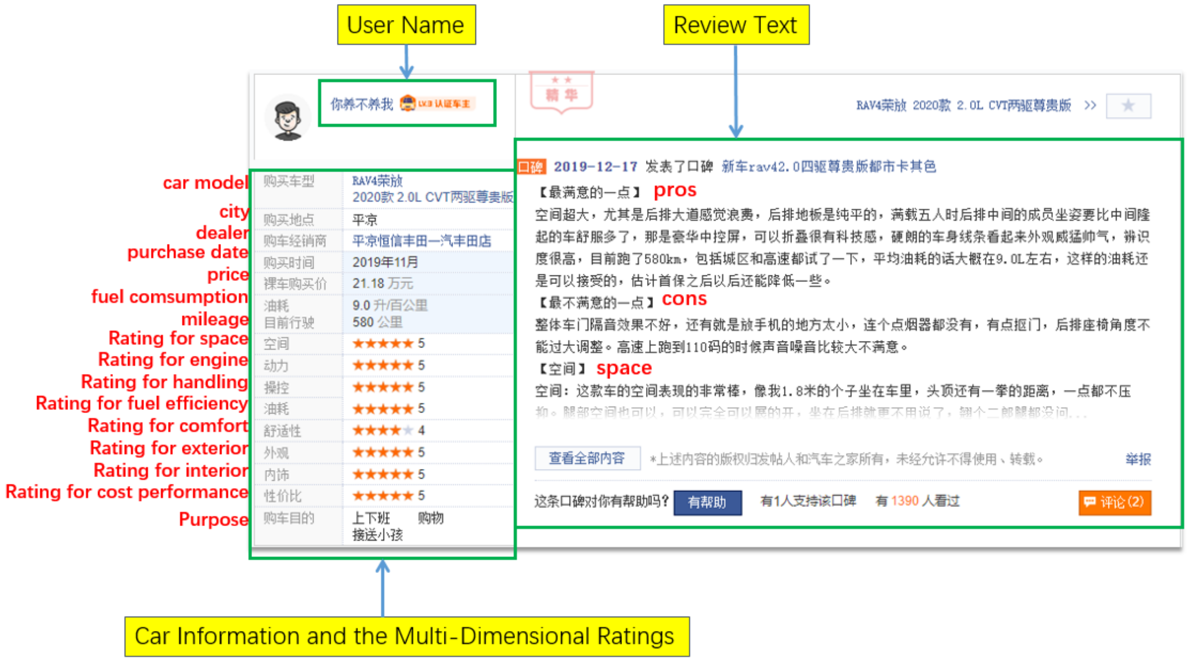


Figure 2: Example of Car Reviews for Toyota RAV4


Figure 3: Overall Rating and Number of Reviews for Toyota RAV4

The car sales data are collected from the China Securities Market & Accounting Research (CSMAR) database. The CSMAR database is jointly built by GTA Information Technology Co. Ltd., the University of Hong Kong, and the China Accounting and Finance Research Center at Hong Kong Polytechnic University.

The car sales data are monthly levels, and the eWOM and search volume index are daily levels. The data from multiple sources are then merged on a monthly basis. After data screening and cleaning, our sample period is from January 2013 to October 2017. Finally, we build a panel dataset with 14,727 observations of 409 passenger car models.

### 3.2 Variables

The dependent variable in this study is *Sales*. We use the sales of a given car model in month $t$ to measure car sales. The independent variable is *Volume*. We assume that car sales are affected by the last month's eWOM volume, i.e., the prediction time window is $t+1$. Hence, we use the number of online car reviews in the last month to measure eWOM volume. The moderating variables are *Domestic*, *TotalSales* and *Price*. *Domestic* is a dummy variable that indicates whether a car brand is domestic or foreign. *TotalSales* is measured by the cumulative sales of a given car until the last month. In addition to the independent and moderating variables, we control for other factors that may impact car sales. The control variables include eWOM rating, fuel efficiency, rating of a dealer, and search interests. These variables are measured as the average value of car $i$ in month $t$. The detailed definitions of these variables are summarized in Table 1.

Table 1: Definitions of the Main Variables and Data Sources

| **Variable** | **Measure** | **Data Source** |
|---|---|---|
| Dependent Variable | | |
| $Sales_{it}$ | Sales of car $i$ in month $t$. The log value is used in the regressions. | CSMAR |
| Independent Variable | | |
| $Volume_{i(t-k)}$ | Volume of word-of-mouth regarding car $i$ in month $t$-$k$. The log value is used in the regressions. | Autohome |
| Moderating Variables | | |
| $Foreign_i$ | Dummy variable that equals 1 if the brand is foreign and 0 if the brand is domestic. | Autohome |
| $Price_{it}$ | Average actual purchase price of car $i$ in month $t$. The log value is used in the regressions. | Autohome |
| $TotalSales_{it}$ | Cumulative sales of car $i$ until month $t$-$1$. The log value is used in the regressions. | Autohome |
| Control Variables | | |
| $SearchVol_{i(t-k)}$ | Search volume reported by Baidu for car $i$ in month $t$-$k$. The log value is used in the regressions. | Autohome |
| $Rating_{i(t-k)}$ | Average rating of car $i$ in month $t$-$k$. The log value is used in the regressions. | Autohome |
| $Age_{it}$ | Number of months from the launch of car $i$. The log value is used in the regressions. | Autohome |
| $FuelEff_{it}$ | Average fuel efficiency of car $i$ in month $t$. The log value is used in the regressions. | Autohome |
| $DealerRat_{it}$ | Average rating of dealers of car $i$ in month $t$. The log value is used in the regressions. | Autohome |

### 3.3 Model Specification

To test our hypothesis regarding the relationship between the volume of word of mouth and car sales, we first develop a multivariate regression model, as shown in Equation (1). All variables in Equation (1) are defined in Table 1.

$$\begin{aligned} Sales_{it} &= \beta_0 + \beta_1 Volume_{i(t-k)} + \beta_2 Rating_{i(t-k)} + \beta_3 Price_{it} + \beta_4 TotalSales_{it} \\ &+ \beta_5 Volume_{i(t-k)} * Price_{it} + \beta_6 Volume_{i(t-k)} * Foreign_i + \beta_7 Volume_{i(t-k)} * TotalSales_{it} \\ &+ \beta_8 Age_{it} + \beta_9 SearchVol_{i(t-k)} + \beta_{10} FuelEff_{it} + \beta_{11} DealerRat_{it} + p_i + f_t \end{aligned} \quad (1)$$

We note the timing difference between car sales and online WOM. Because consumer reviews on Autohome reflect the experiences of prior customers, and it is difficult to determine whether these reviews were posted before sales in the same month, we assume that online WOM impacts car sales in the following month.

In addition to the eWOM effects and network effects, production diffusion may affect buyers' purchase decisions. To control for production diffusion, we follow Duan et al. (2009) and control for product age ($Age_{it}$) in the empirical model.

Prior studies have found that eWOM not only drives retail sales but is also an outcome of retail sales (Duan et al., 2008b; Godes & Mayzlin, 2004). This dynamic relationship raises concerns regarding the endogeneity between eWOM and sales. According to Gu et al. (2012), major factors contributing to the endogeneity problem are product characteristics and demand shocks, which have the potential to affect both product sales and eWOM.

To address the endogeneity problem, we further employ a two-way fixed effect model to control for both product and time fixed effects. We include product fixed effects $p_i$ to control for both observed and unobserved differences across products and time-specific fixed effects $f_t$ to control for time-variant factors (e.g., seasonality).

According to Gu et al. (2012), another major factor contributing to the endogeneity problem is demand shocks (such as those caused by advertising). Such demand shocks could result in endogeneity between product sales and eWOM volume. Following Gu et al. (2012), unobserved demand shocks can be addressed by introducing the Baidu search index (*SearchVolume*) as a control variable.

## 4. Empirical Results

### 4.1 Descriptive Statistics

The descriptive statistics and correlation matrix of the main variables used in this study are provided in Table 2 and Table 3. To reduce skewness, the log values of the variables are used.

Table 2: Descriptive Statistics

| Variable | Obs. | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|---|
| *Sales* | 14,727 | 7.72 | 1.68 | 0 | 11.29 |
| *Volume* | 14,756 | 3.12 | 1.37 | 0 | 6.71 |
| *Rating* | 14,756 | 1.43 | 0.08 | 0 | 1.60 |
| *Price* | 14,756 | 2.41 | 0.57 | 0 | 4.38 |
| *Foreign* | 14,756 | 0.45 | 0.49 | 0 | 1 |
| *Age* | 14,674 | 3.68 | 1.08 | 0 | 5.36 |
| *TotalSales* | 14,347 | 0.36 | 0.06 | -1.49 | .47 |
| *SearchVol* | 14,347 | 11.10 | 1.18 | 4.18 | 15.57 |
| *FuelRff* | 14,700 | 2.06 | 0.23 | 0 | 2.99 |
| *DealerRat* | 14,756 | 1.42 | 0.11 | 0 | 1.60 |

Table 3 provides the correlation matrix and variance inflation factor (VIF) values of the key variables in our study. As shown in Table 3, the correlations between each pair of variables are small, except for the correlations between *Sales* and *Volume* (0.682) and *Price* and *FuelEff* (0.701). To avoid multicollinearity, we calculate the VIFs of all independent variables. Table 3 shows that the maximum VIF is below 5, indicating that no severe multicollinearity exists (Mason & Perreault Jr, 1991).

Table 3: Correlation Matrix and VIFs of the Main Variables

| Variable | *Sales* | *Volume* | *Rating* | *Price* | *TotalSales* | *Age* | *Foreign* | *SearchVol* | *FuelEff* | *DealerRat* |
|---|---|---|---|---|---|---|---|---|---|---|
| *Sales* | 1.000 | | | | | | | | | |
| *Volume* | 0.682 | 1.000 | | | | | | | | |
| *Rating* | 0.218 | 0.335 | 1.000 | | | | | | | |
| *Price* | 0.148 | 0.173 | 0.387 | 1.000 | | | | | | |
| *TotalSales* | 0.569 | 0.530 | 0.025 | 0.028 | 1.000 | | | | | |
| *Age* | 0.025 | 0.053 | -0.314 | -0.053 | 0.443 | 1.000 | | | | |
| *Foreign* | 0.279 | 0.322 | 0.145 | 0.528 | 0.265 | 0.241 | 1.000 | | | |
| *SearchVol* | 0.562 | 0.575 | 0.276 | 0.238 | 0.418 | -0.029 | 0.202 | 1.000 | | |
| *FuelEff* | -0.038 | 0.003 | 0.197 | 0.701 | -0.110 | -0.047 | 0.186 | 0.058 | 1.000 | |
| *DealerRat* | 0.121 | 0.172 | 0.233 | 0.171 | 0.051 | -0.089 | 0.111 | 0.157 | 0.045 | 1.000 |
| VIF | | 2.04 | 1.52 | 3.51 | 1.98 | 1.59 | 1.84 | 1.66 | 2.29 | 1.09 |

### 4.2 Main Results

We employ the interactions between eWOM *volume* and *Foreign*, *Price*, as well as *TotalSales* to capture their joint effects on sales in the context of high-involvement products. A two-way fixed effect model is adopted to estimate the parameters in Equation (1). Table 4 presents the results of the stepwise regressions. The coefficient of *Volume* is significantly positive across the four models, providing additional evidence for the argument that eWOM volume is helpful in promoting sales. Hypothesis 2 is also supported by Model 2, Model 3 and Model 4. The significantly negative coefficient of *Volume*Price* indicates that the eWOM effect is less influential among more expensive automobiles. Although the eWOM volume of automobiles promotes sales, a higher price may interfere with benefit-cost analysis and impede consumers' purchase intention. As shown in Model 3 and Model 4, the coefficients of *Volume* TotalSales* are significantly positive, suggesting that the network effects enhance the positive influence of the volume of eWOM on automobile sales, supporting hypothesis 3. Similarly, the significant positive coefficient of the interaction term between *Volume* and *Foreign* indicates that the eWOM effect is more influential among foreign brand automobiles than domestic brand automobiles, supporting hypothesis 4.

Regarding the control variables, *Rating* and *SearchVol* are positively related to automobile sales, suggesting that automobiles with more attention and better reputation may experience larger sales. However, *FuelEff* and *Price* are negatively related to automobile sales, indicating that consumers are concerned about cost. In addition, consistent with previous studies (Katz & Shapiro, 1985, 1994), the coefficients of *TotalSales* are significantly positive in all models, demonstrating the network effect in the automobile market.

Table 4: Effect of the Review Volume on Automobile Sales (*T*+1)

| Variable | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| *Volume* | 0.464 (0.010)$^{***}$ | 0.657 (0.041)$^{***}$ | 0. 382 (0.072)$^{***}$ | 0.594 (0.076)$^{***}$ |
| *Volume*Price* | | **-0.082 (0.017)$^{***}$** | **-0.068 (0.017)$^{***}$** | **-0.159 (0.020)$^{***}$** |
| *Volume*TotalSales* | | | **0.022 (0.004)$^{***}$** | **0.014 (0.004)$^{***}$** |
| *Volume *Foreign* | | | | **0.194 (0.022)$^{***}$** |
| *Rating* | 0.420 (0.122)$^{***}$ | 0.396 (0.122)$^{***}$ | 0.398 (0.122)$^{***}$ | 0.436 (0.121)$^{***}$ |
| *Price* | -0.021 (0.093) | 0.123 (0.097) | 0.097 (0.097) | 0.239 (0.098)$^{**}$ |
| *TotalSales* | 0.015 (0.014)$^{***}$ | 0.021 (0.012)$^{*}$ | -0.049 (0.019)$^{*}$ | -0.024 (0.020)$^{***}$ |
| *Age* | -0.331 (0.023)$^{***}$ | -0.336 (0.023)$^{***}$ | -0.330 (0.023)$^{***}$ | -0.345 (0.023)$^{***}$ |
| *SearchVol* | 0.321 (0.017)$^{***}$ | 0.322 (0.017)$^{***}$ | 0.312 (0.017)$^{***}$ | 0.316 (0.017)$^{***}$ |
| *FuelEff* | -0.086 (0.059) | -0.084 (0.059) | -0.073 (0.059) | -0.075 (0.059) |
| *DealerRat* | 0.082 (0.066) | 0.078 (0.066) | 0.077 (0.066) | 0.091 (0.065) |
| *Product Fixed Effect* | Yes | Yes | Yes | Yes |
| *Time Fixed Effect* | Yes | Yes | Yes | Yes |
| Intercept | 3.261 (0.398)$^{***}$ | 2.918 (0.404)$^{***}$ | 3.768 (0.443)$^{***}$ | 3.052 (0.450)$^{***}$ |
| Obs. | 14,271 | 14,271 | 14, 271 | 14,271 |
| R-squared | 0.266 | 0.267 | 0.268 | 0.272 |

Notes: Standard errors are shown in parentheses; $^{***}$: $p<0.01$, $^{**}$: $p<0.05$, $^{*}$: $p<0.1$.

## 4.3 Robustness Checks

We assume that review volume impacts sales in the following month (i.e., the prediction window is *t+1*) in our primary analysis. To check the robustness of our results, we repeat the multiple linear regression models with fixed effects in various prediction windows (i.e., *t+2*, *t+3*, and *t+4*). The results are reported in Table 5. The coefficients of eWOM volume in Table 5 remain significantly positive, suggesting that eWOM volume affects sales in the following months; however, its effectiveness fades over time. More importantly, a battery of robustness checks demonstrates that the moderating effects are robust across various prediction windows. A higher price may impair the effect of eWOM volume on sales, while foreign brands and user networks may amplify this effect.

Table 5: Effects of Review Volume on Automobile Sales Across Different Prediction Windows

| Variable | Model 2 (*t+2*) | Model 3 (*t+3*) | Model 4 (*t+4*) |
|---|---|---|---|
| *Volume* | 0.494 (0.077)*** | 0.457 (0.080)*** | 0.394 (0.082)*** |
| *Volume*Price* | **-0.168(0.021)***** | **-0.161(0.021)***** | **-0.143(0.022)***** |
| *Volume*TotalSales* | **0.023(0.005)***** | **0.023(0.005)***** | **0.024(0.005)**** |
| *Volume*Foreign* | **0.201(0.023)***** | **0.196 (0.024)***** | **0.185(0.025)***** |
| *Rating* | 0.380(0.126)*** | 0.604(0.131)*** | 0.385(0.136)*** |
| *Price* | 0.174(0.100)* | 0.176(0.102)* | 0.129(0.105) |
| *TotalSales* | -0.099(0.020) *** | -0.123(0.021)*** | -0.134(0.021)*** |
| *Age* | -0.364(0.027)*** | -0.385(0.030)*** | -0.445(0.033)*** |
| *SearchVol* | 0.314(0.017)*** | 0.312(0.018)*** | 0.300(0.018)*** |
| *FuelEff* | -0.110(0.0601)** | -0.102(0.062) | -0.116(0.064)* |
| *DealerRat* | 0.098(0.067) | 0.182(0.068)*** | 0.191(0.069)*** |
| *Product Fixed Effect* | Yes | Yes | Yes |
| *Time Fixed Effect* | Yes | Yes | Yes |
| Intercept | 4.359 (0.459)*** | 4.322 (0.477)*** | 5.278 (0.483)** |
| Obs. | 13,866 | 13,458 | 13,051 |
| R-squared | 0.266 | 0.254 | 0.243 |

Notes: Standard errors are reported in parentheses; ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$.

## 5. Conclusion

To better understand the underlying mechanism regarding how eWOM interplays with traditional product signals in high-involvement product marketing, we conduct an empirical investigation based on a dataset collected from Autohome, CSMAR, and Baidu. A two-way fixed effect panel model is employed to examine the joint effect of eWOM and price, brand origin, as well as the number of users. Our empirical results confirm the positive effect of eWOM volume on sales in the context of high-involvement products, and the effects of eWOM volume on future sales are moderated by the abovementioned product signals. Specifically, the impact of eWOM volume on sales is negatively moderated by price. In contrast, the number of customers and foreign brands enhances the effect of eWOM on sales. In addition, additional analysis with various prediction windows proves that our findings are robust. Our empirical results support the view that the influence of eWOM on product sales depends on product signals. Therefore, firms' eWOM management strategies need to be adjusted accordingly.

## 6. Discussion

The principal objective of this study is to examine the moderating effects of three traditional product signals (i.e., price, brand origin, and the number of customers) on the relationship between eWOM and sales in the context of high-involvement products. This research contributes to the current literature on eWOM in the following ways. First, this study provides a potential explanation of the previous mixed results regarding the relationship between eWOM and product sales. Although prior research has provided early evidence of the influence of eWOM on product sales. Our research goes a step further and provides deep insight into the impact mechanism of eWOM. Second, the results also highlight the role of product involvement in eWOM research. There are significant differences in information searching behavior in the purchase decision process between high-involvement products and low-involvement products. It is necessary to consider product involvement in understanding online consumer information search behavior and its influence on retail strategies.

The results also have valuable practical implications. First, the results of this study help car manufacturers comprehensively and deeply understand the impact mechanism of eWOM on product sales and provide the implication that there is no one-size-fits-all strategy of eWOM management in marketing. Specifically, compared to popular foreign brands with beautiful prices, niche domestic brands with higher prices should devote more effort to increasing eWOM to promote sales. Second, online review platforms can optimize their design to improve the helpfulness of platforms and attract more user registration based on our findings. The integration of eWOM and traditional product signals caters to multiple information requirements of purchase decisions. Furthermore, a screener based on the combination of eWOM and product features would be even better.

This study also has several limitations that deserve future research efforts. First, eWOM and alternative information cues may affect consumer behavior more complicatedly than we expect in this study. Therefore, more effort is required to elaborate the mechanism by which eWOM and confounding factors affect consumer behavior. Second, because of data limitations, we only focus on one example of high-involvement products (i.e., cars). Obviously, there are other types of high-involvement products, such as household home appliances and consumer electronics. Therefore, further studies are necessary to generalize our findings to different contexts. Third, the effects of eWOM marketing may be contingent on national culture; consumers in the Chinese market may behave differently from consumers in other markets where passenger cars are an essential product for daily life. Therefore, it is interesting to study the moderating effects in developed countries such as Japan, Germany and the USA, which have a more mature automobile culture, premium car manufacturing capacity and car brand loyalty.

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