The Influence of The Volume and The Valence of Online Reviews: A Dynamic Panel Data Analysis

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Abstract:

The aim of this research is to examine the effects of the volume and the valence of online reviews on product sales. In order to do that, panel data has been collected from Amazon.com with the help of a specifically developed software. The sample consists of brands including furniture, laptop, dental care, and TV categories. Generalized Method of Moments (GMM) models are utilized as analytical tools. The first model reveals that volume has a significant negative effect referring an inverse relationship between sales and volume. The effect of valence is found to be mixed. In terms of valence, whereas negativity of reviews effects sales, however, the average rating does not have any influence. The second model, consisting the moderating effects of product categories, reveals that the influences of both volume and valence variables vary for each product category.

Keywords:volume, valence, GMM

Track: Digital Marketing & Social Media

1. Introduction

Humankind has used word of mouth (WOM) communication as one of the most powerful sources of information since the beginning of the society (Reynolds & Beatty, 1999; Maxham & Netemeyer, 2002; Godes & Mayzlin, 2004). WOM commonly refers to "all informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services or their sellers” (Westbrook, 1987). Affecting consumers' awareness, expectations, perceptions, attitudes, behavioral intentions, and behavior (Buttle, 1998) WOM has a greater impact on consumers than other types of marketing communications (Day, 1971).

Developments in information technology and the Internet has evolved WOM to the next level, moved it to the online world, and made WOM messages to be conveyed worldwide (Laroche, Yang, McDougall, & Bergeron, 2005). The new version of WOM, electronic word of mouth (eWOM) is defined by Hennig-Thurau, Gwinner, Walsh, and Gremler, (2004) as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet". Consumers may be exposed to eWOM through websites, forums, blogs, email, or social media.

Online reviews are the eWOM messages on websites of e-retailers. Online reviews are one of the powerful channels to generate eWOM (Duan, Gu, & Whinston, 2008). Many of the e-retailers, even the smallest ones, allow consumers to post online reviews for the products they offer (Gupta & Harris 2010). With its review system, Amazon.com might be called the leader of e-retailers. More than half of consumers in the USA start their information search on Amazon, even they are standing inside a store at that moment (Weise, 2017). Therefore, Amazon has been subject to eWOM researches focusing on the relation between sales and online reviews (Chevalier & Mayzlin, 2006; Gu, Tang & Whinston, 2013).

In this research, to examine the influence of online reviews on sales, data collected from Amazon.com is analyzed. The sample includes products from four product categories; furniture, TV, laptop, and dental care. The data is considered as dynamic panel data, and Generalized Method of Moments (GMM) model is used as the estimation method.

2. Theoretical Background and Research Objectives

In WOM literature, two characteristics of WOM, the volume and the valence have attracted considerable attention (Cheung & Thadani, 2012). The amount of WOM disseminated refers to the volume of WOM (Duan et al., 2008). In the context of eWOM, the volume is the number of reviews about a product. Volume has the power to create awareness for the product which will consequently result in higher sales (Godes & Mayzlin, 2004) and studies found that volume has significant effects on sales (e.g. Chen, Wu, & Yoon 2004; Liu 2006; Duan et al., 2008; Davis & Khazanchi, 2008). Although the results of many studies indicate the impact of volume, there are also studies finding the insufficiency of the volume itself (e.g. Chintagunta, Gopinath, & Venkataraman, 2010). Another aspect of volume is that volume and sales have a two-way relationship. The volume is not only the cause of customer purchase but also the outcome of sales (Godes & Mayzlin, 2004). In other words, by turns, more WOM generate more sales, and more sales generate more WOM (Duan et al., 2008).

The valence of WOM is measured by percentages of positive and negative messages (Liu, 2006). The negative messages are acknowledged as to be more influential than positive messages (Chatterjee, 2001). Many of the online retailers make it possible for consumers to summarize their reviews via numbers or stars (e.g. 1 star for "very bad" and 5 stars for "very good"), and the mean average of these ratings reflects the valence. The mean rating is assumed to be a proxy for product quality (Hu, Pavlou, & Zhang, 2017). Thereby, many researchers hypothesise that the valence has a significant impact on sales (e.g. Chevalier & Mayzlin, 2006; Liu, 2006; Gu et al., 2013). While, the results of some studies reveal the relationship between valence and sales (Chevalier & Mayzlin, 2006; Gu et al., 2013), the results of some other studies do not support the effects of the valence (Liu, 2006). Duan et al. (2008) found an indirect effect of the valence on box office revenues by generating a higher volume of WOM.

The main research objective is to examine the effects of the volume and valence of online reviews on product sales. For this purpose, we developed the following research questions:

RQ1: Does the volume of reviews have an influence over the sales?

RQ2: Does the effect of the volume on the sales vary based on product categories?

RQ3: Does the valence of reviews have an influence over the sales?

RQ4: Does the effect of the volume on the sales vary based on product categories?

3. Research Methodology

3.1. Data set, variables, and emprical model development

We collected publicly available data from Amazon for 31 weeks, from July 2017 to February 2018. We gathered the data weekly via a data mining program specially developed for this research. The sample includes totally 172 products in four product categories (laptop, tv, furniture, and dental care products). For each product, we obtained sales rank in the product category, price, discount rate, number of total reviews, the average[1] rating of reviews, and the percentages of each star ratings. Table 1 summarizes the descriptive statistics of the data set.

	N	Min.	Max.	Mean	Median	Std. Deviation
Product	172	NA	NA	NA	NA	NA
Product Category	4	1	4	NA	NA	NA
Sales Rank		1	12923642	901084.6	103452.5	1467813
Price ($)		10.49	8998	703.9555	369	865.6316
Discount Rate (%)		0	96	6.104651	0	12.05955
Total Reviews		0	2982	247.9012	47	475.7213
Average Rating		0	5	3.734771	4	1.043803
One Star Ratings (%)		0	100	12.62509	11	13.68623
Two Star Ratings (%)		0	100	5.497562	4	7.333738
Three Star Ratings (%)		0	100	7.914666	7	9.862972
Four Star Ratings (%)		0	100	15.64254	15	13.52619
Five Star Ratings (%)		0	100	53.68773	56	22.91335

Table 1. Descriptive statistics of the data set

Amazon provides sales rank of product rather than quantity of sales. Rank reflects the quantity as lower the sales higher the rank (Chevalier & Mayzlin, 2006), and the dependent variable is $\ln(\text{Rank}_{it})$. $\ln(\text{Price}_{it})$ and Discount_{it} are control variables. TotalReview_{it} is the endogenous variable reflecting the volume of reviews. Lastly, Rating_{it}, Bad_{it}, Neutral_{it}, and Good_{it} are explanatory variables reflecting the valence of the reviews. Table 2 provides variables used in emprical analysis and their descriptions.

Variable	Description
$\ln(\text{Rank}_{it})$	Natural logarithm of sales rank of product *i* at week *t*
$\ln(\text{Price}_{it})$	Natural logarithm of price of product *i* at week *t*
Discount_{it}	Discount rate for product *i* at week *t*
TotalReview_{it}	Number of total reviews for product *i* until week *t*
Rating_{it}	Average rating for product *i* at week *t*
Bad_{it}	Total percentages of one star and two star ratings for product *i* until week *t*
Neutral_{it}	Percentage of three star ratings for product *i* until week *t*
Good_{it}	Total percentages of four star and five star ratings for product *i* until week *t*
Category_{j}	Product category dummies
Furn_{i}	A dummy variable indicating if product *i* is a furniture (coded as 1 if product is a furniture, 0 otherwise)
TV_{i}	A dummy variable indicating if product *i* is a TV (coded as 1 if product is a TV, 0 otherwise)
Laptop_{i}	A dummy variable indicating if product *i* is a laptop (coded as 1 if product is a laptop, 0 otherwise)
DCare_{i}	A dummy variable indicating if product *i* is a dental care product (coded as 1 if product is a dental care product, 0 otherwise)

Table 2. Variables and descriptions

[1] We call it "average rating", however Amazon states that it is not calculated as a raw data average. This rating is calculated based on a machine learned model which takes into account factors including the age of a rating, whether the ratings are from verified purchasers, and factors that establish reviewer trustworthiness.

Simultaneous causality between sales and WOM (Godes & Mayzlin, 2004; Duan et al., 2008) leads to endogeneity bias. For dynamic panel data, GMM model which is developed by Arellano and Bond (1991) can be used to deal with endogeneity bias (Zaefarian, Kadile, Henneberg, & Leischnig, 2017). In GMM models, lags of dependent variables are used as explanatory variables (Ullah, Akhtar, & Zaefarian, 2018). Thus, we developed the following model to estimate sales rank:

$$\begin{aligned}\Delta ln(Rank_{it}) = \beta_1 * \Delta ln(Rank_{it-1}) + \beta_2 * \Delta ln(Rank_{it-2}) + \beta_3 * \Delta ln(Price_{it}) + \beta_4 \\ * \Delta Discount_{it} + \beta_5 * \Delta Rating_{it} + \beta_6 * \Delta TotalReview_{it} + \beta_7 * \Delta Bad_{it} \\ + \beta_8 * \Delta Neutral_{it} + \beta_9 * \Delta Good_{it} + \varepsilon_{it}\end{aligned} \tag{1}$$

To analyze whether the effects of the volume and valence of eWOM change based on product categories, we multiplied volume and valence variables with product category dummies (*category*$_j$). By being added *category*$_j$, the model takes the form of the following equation (2):

$$\begin{aligned}\Delta Ln(Rank_{it}) = \beta_1 * \Delta Ln(Rank_{it-1}) + \beta_2 * \Delta ln(Rank_{it-2}) + \beta_3 * \Delta ln(Price_{it}) + \beta_4 \\ * \Delta Discount_{it} + \beta_5 * \Delta(Rating_{it} * Category_j) + \beta_6 * \Delta(TotalReview_{it} \\ * Category_j) + \beta_7 * \Delta(Bad_{it} * Category_j) + \beta_8 * \Delta(Neutral_{it} \\ * Category_j) + \beta_9 * \Delta(Good_{it} * Category_j) + \varepsilon_{it}\end{aligned} \tag{2}$$

3.2. Results and Discussion

Table 3 presents the results of system GMM models of online reviews and sales rank. We examine AR(1) and AR(2) statistics to test for serial correlation in the error terms. The null hypothesis of AR(1) is that there is no first-order serial correlation, and the null hypothesis of AR(2) is that there is no second-order serial correlation. The system GMM assumes that first-order serial correlation is present but the second-order serial correlation is not (Arellano and Bond 1991). Our results reject the null hypothesis of AR(1), but fail to reject the null hypothesis of AR(2).

We examine Hansen J-statistics to test for validity of instruments. The null hypothesis of Hansen J-stat is that the overidentification restrictions are valid. Our results fail to reject the null hypothesis of Hansen J-stat and support the validity of instruments in our models.

Dep. Variable: *ln(Rank$_{it}$)*	**Model (1)**		**Model (2)**	
Variables	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
ln(Rank$_{it-1}$)	.352576***	.002251	.300600***	.009822
ln(Rank$_{it-2}$)	.110182***	.001896	.078861***	.004278
ln(Price$_{it}$)	.698090***	.024649	.765541***	.091575
Discount$_{it}$	-.006557***	.000694	-.007220***	.001311
TotalReview$_{it}$	.001523***	9.28e-05		
Rating$_{it}$	-.013165	.031405		
Good$_{it}$	-.010852***	. 001184		
Neutral$_{it}$	-.011263***	.001868		
Bad$_{it}$	omitted			
*Furn$_i$ * TotalReview$_{it}$*			.025666***	.003986
*Laptop$_i$ * TotalReview$_{it}$*			.001397*	.000616
*DCare$_i$ * TotalReview$_{it}$*			.000292	.001032
*TV$_i$ * TotalReview$_{it}$*			.000484	.001182
*Furn$_i$ * Rating$_{it}$*			.019893	.182989
*Laptop$_i$ * Rating$_{it}$*			.035052	.536035
*DCare$_i$ * Rating$_{it}$*			7.229673	5.930929
*TV$_i$ * Rating$_{it}$*			-1.398856***	.365060
*Furn$_i$ * Good$_{it}$*			-.003446	0.010264
*Furn$_i$ * Neutral$_{it}$*			-.017241*	.008880
*Furn$_i$ * Bad$_{it}$*			omitted	
*Laptop$_i$ * Good$_{it}$*			-.049443**	.017528
*Laptop$_i$ * Neutral$_{it}$*			-.055969	.039095
*Laptop$_i$ * Bad$_{it}$*			omitted	
*DCare$_i$ * Good$_{it}$*			.587492	.405433
*DCare$_i$ * Neutral$_{it}$*			.655550	.422234
*DCare$_i$ * Bad$_{it}$*			omitted	
*TV$_i$ * Good$_{it}$*			.024225*	.012378
*TV$_i$ * Neutral$_{it}$*			.038461*	.018774
*TV$_i$ * Bad$_{it}$*			omitted	
No. of observations	4816		4816	
No. of groups	172		172	
No. of instruments	172		172	
p value of AR(1)	.0000		.0017	
p value of AR(2)	.1027		.8888	
p value of Hansen J test	.438546		.390613	

* p<.05 ,** p<.01, *** p<.001

Note: To prevent "near singular matrix" error, we omitted *Bad$_{it}$* , *Furn$_i$ * Bad$_{it}$* ,*Laptop$_i$ * Bad$_{it}$* ,*DCare$_i$ * Bad$_{it}$* , *and TV$_i$ * Bad$_{it}$* from both equations.

Table 3. System GMM models of online reviews and sales rank

In both models, sales ranks in previous periods and the price have a positive effect on the sales rank. Also, the discount rate has a negative effect on the sales rank. In the first model, the total review has a positive effect on sales rank, indicating that product sales decreases as the volume of reviews increases. On the other hand, the effect of the average rating is not significant. The effects of good and neutral ratings are significantly different than the effect of bad ratings, indicating that product sales increases as the percentage of bad rating decreases.

In model 2, we analyze the moderating effect of product categories on volume and valence variables. In terms of volume, two of product categories (furniture and laptop) have a significant moderating effect, and the other two categories (dental care and TV) have no significant moderating effect. In other words, if the product is a furniture or laptop, sales increases as the volume of reviews decreases. On the other hand, if the product is a dental care product or TV, sales do not significantly change as the volume of reviews changes.

Regarding the valence variables, only moderating effect of TV category is significant, indicating that if the product is a TV, sales increases as the average rating increases. Besides, if the product is a furniture, laptop or dental care product, sales do not significantly change as the average rating changes.

Examining the effects of other valence variables (good, bad, neutral), it is realized that significances of differences in effects change for each category. For furniture category, the effect of the good rating is not significantly different than the effect of bad rating, whereas the effect of the neutral rating is significantly different than the bad rating. This indicates that if the product is a furniture, sales increases as the percentage of neutral rating increases. For the laptop category, the effect of the good rating is significantly different than the effect of bad rating, however, the effect of the neutral rating is not significantly different than the bad rating. In other words, if the product is a laptop, sales increases as the percentage of good rating increases. For dental care product category, the effects of good and neutral ratings are not siginificantly different than the effect of bad rating. Finally, for TV category, the effects of good and neutral ratings are significantly different than the effect of bad rating, indicating that if the product is a TV, sales increases as the percentage of bad rating increases.

4. Conclusion

In this research, it is aimed to examine the influence of the volume and the valence of online reviews on sales. For this purpose, GMM models are utilized to analyze the panel data collected from Amazon.com. In the first model, data is analyzed as a whole without the moderating effect of the product categories. In the second model, the moderating effect of the product categories is added to the model to analyze whether the influence of volume and valence variables change based on product categories.

Our first model suggests that the volume positively influence sales rank. However, this refers that the inverse relationship between sales and volume since, higher sales indicates lower ranks. Though the literature provides evidence about a positive relationship between volume and sales (e.g. Liu, 2006), our findings do not support this view. This may be caused by moderating variable; category. While furniture and laptop categories volume has a significant negative influence on sales, this influence may not be found in dental care and TV categories.

The influences of the valence variables are mixed according to the results of both models. The results of the first model reveal a significant difference between bad reviews and good reviews. However, the average rating does not have an influence on sales. Besides, according to the results of the second model, the effects of valence variables vary for each product category.

We assume that Amazon customers solely rely on reviews on Amazon.com regarding required information for decision making. Nevertheless, this is not the case in real life but customers have many online and offline information sources.

This study contributes to the current literature in that the influence of online reviews in terms of volume and valence vary regarding product categories. While for some categories valence has influence over sales, for other categories volume some influences. For laptop category for instance both volume and valence influence the sales.

Further research is needed to be done for the product categories included in this study. Especially the effect of the volume needs to be focused. It should be clarified that whether the negative relationship between the volume and sales is because of the product category or because of the sample itself.

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