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The Analysis of E-product Sales Affected by Online Word-of-Mouth and E-commerce Service Quality Based on Observational Learning

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ABSTRACT

Information on product sales pages is an important role in consumers' purchase decisions in e-commence. This paper study two categories of information, online word-of-mouth (WOM) and E-commerce service quality (e-SQ) based on observational learning (OL), by data from the largest B2C platform- Alibaba.com. Our study adopts panel vector auto-regression (PVAR) model to explore the dynamic interactive effects among product sales, WOM and E-SQ OL. We investigate the forecast capability among product sales, online reviews of WOM and OL information about e-SQ through impulse response function analysis and forecast error variance decomposition. The findings are interesting and useful for real e-business.

KEYWORDS: Online word-of-mouth, Online observational learning, E-commerce service quality, Panel vector auto-regression.

INTRODUCTION

Over the last few years, online shopping has become more and more popular, especially for large online shopping mall (such as Amazon.com,Tmall.com). And their reputation and quality assurance are extensively accepted by consumers. Faced with a superb collection of online products, consumers are more likely to rely on the information in product sales page, in order to save time and reduce the risk of purchase (Bikhchandani et al., 1998). Among the tremendous information shown on page, online word-of-mouth (WOM) and online observation learning (OL) are two kinds of vital user-generated information. The extant researches have shown that compared to the traditional marketing activities, the user-generated information is more powerful in the choice behavior on subsequent consumers (Trusov et al., 2009).

In the field of marketing, the social interaction based on opinion or perference is called WOM (Arndt, 1967). And it is named as online WOM if the information is disseminated through network media (Godes et al., 2005). In the field of psychology and economics, the social interaction based on action or behavior is called OL (Bandura, 1977; Bikhchandani et al, 1998). For example, when making choice between two restaurants, customers might be greatly influenced by their friends advice or just simply observate the number of persons who are having meals in each restaurant, even they have own standards and reasons to choose restaurant (Becker, 1991). When this observation is based on metword information, it is named as online OL. The difference between online OL and WOM is mainly reflected in two aspects of information quantity and credibility in the socail interaction. Compared with the latter, the former contains less information (Chen et al., 2011). Bikhchandani (1998) pointed out that online WOM usually includes consumer advice or recommendation (eg. five star review), also the reasons about making a certain evaluation such as describing the use experiences about product. While online OL only reveals the comprehensive results of other consuming behaviors about some product such as appearing on sales ranking list, but does not provide the reasons leading to the result.

In this paper, we will focus on the information of online comments based WOM and E-commerce service quality (e-SQ) based OL. Online comments play an important role in shaping consumers' attitudes and buying behavior which will have influence on the sales of products (such as Chevalier and Mayzlin, 2006). As a special OL information , e-SQ has significant impact on consumers' satisfaction and purchase intention (such as Ho and Lee, 2007). This means that the two types of information have effects on the sales of products both directly and indirectly. So, it is worth to study weather the three elements have dynamic interactions between each other.

In recent years, some scholars have studied the dynamic interaction between the sales of products (or sales) and online WOM. Duan et al.(2008) and Lu et al.(2013) treat the box office and the restaurant income as the research object respectively and fond the dynamic interaction between consumers' offline behavior and online WOM. Different frome this papers, our study based on large B2C electric business platform and reveals the dynamic interaction between online WOM and consumers' noline behaviors. For the empirical model, Some literatures rely on Vecror Auto-Regression (VAR) to analyze the dynamic interaction between online WOM and consumers' behaviors using long time series data of one product (such as stock, new menber registration, constomer value growth) (Luo, 2009; Tirunilla and Tellis, 2012; Trusov et al., 2009; Villanueva, 2008). However, we employ Panel Vector Auto-Regression (PVAR) model explore the topic with panel data of multiple products. For more details, we use the unique empirical data sources of online comment display and measure the positive WOM with the percentage of positive comments label which are derived by text mining of background system. This may provide more detailed information than previous studies such as Sonnier et al.(2011)and Ho-Dac et al.(2013) which regard five and four stars as positive WOM and three stars as negative WOM.

In addition, some scholars have studied the mutual influence on consumer behavior and e-SQ. Finn(2011) reveals the nonlinear effect of e-SQ index on consumer satisfaction. Delone(2003) found that the information quality and consumers satisfaction were positive related. Udo(2010) found that e-SQ not only had a signigicant direct impact on consumer purchase intention but also had a indirect effect through the consumer satisfaction as the intermediate variable. Olrunniwo(2006) pointed out that the electric service manager should adjust operation strategy to improve service quality, which would have a positive influence on consumer purchase intention. Chang(2009) performed an experiment with questionnaire and found that the electric service quality had an effect on consumer loyalty though consumer satisfaction. This literatures have revealed the impact of e-SQ on consumer satisfaction, purchase intention and loyalty, among which few attention have been paid to the direction relation between e-SQ and product sales. This paper focuses on the impact of e-SQ on product sales with the help of the sales data from larg B2C business platform. In additon, we also study the influence of product sales on e-SQ using dynamic model.

Specifically, the topic studied here can be summarized as follows: whether there are long term dynamic interaction between the information of WOM and e-SQ based online OL? Whether product sales have dynamic feedback effect on the information of WOM and e-SQ based online OL? Is it the dynamic cross effect exist between the two kinds of information? Despite answering the three questions, this study will also explore whether the information of product sales, WOM and online OL can predict each other. Specifically, our studies cover two aspects: 1) The moving trends of the three kinds of information variables in the future period if one of them bear a sudden change at present. 2) what extent will an information variable fluctuation contribute to the three kinds of information variables' future multi period fluctuation (or the ability to explain).

DATA DESCRIPTION and RESEARCH STRATEGY

Data

Our data comes from the largest B2C e-commerce platform of China – tmall.com, whose annual sales is one thousand billion RMB in 2012. This paper use notebook data only in empirical study. By the aid of webpage data collection tool, we grab relavant data in the sales page once a week. In order to assure that all of data are obtained in the same moment which can avoid some deviations resulted by data updating in the page due to customers purchase behaviors, we choose to collect data between am 0 and am 6:00 each time. In this period, the customers seldom go to buy on internet and informaiton on product sales page is relatively static. We have obtain data spanning July 15, 2013 to January 13, 2014 (27 weeks). Throughout this period the produts on the shelf was weekly up dataed frequently, that made the panel data extremely unbanlanced. In this study, we only use the data collected from July 29, 2013 to December 9, 2013 (20 weeks) to include more balanced sample data which is required by the PVAR model used [The 20 weeks sample can be interpreted as the data between the 3rd and the 22nd week of the full sample. The main reason for this refinement is that we didn't get the full data of the first two weeks due to inefficiently use of the software. In addition, Tmall revised its sales page design and product classification in the 23rd week, which resulted in a greater changes of the products. So if we extend panel time span, the sample capacity will become much smaller].

Variable Definition

The study contains 3types of variables: product sales, comments based WOM, e-SQ based online OL information (such as:"Description Accordance" and "Refund Rate")。 The logarithm of product sales ($Ln\_wsales_{i,t}$) represent the logarithm of product *i*'s sales at week *t*.

The logarithm of the change of comment volume ($Ln\_volume_{i,t}$) expresses the logarithm of the incremental number of product *i*'s comments in week *t* compared to week t-1， unlike most studies use total number of comments (log) measure WOM (such as Chevalier and mayzlin, 2006; Gu et al. 2012). We can explain the relationship between sales and comments more precisely with the help of incremental number of comments (log) because the weekly sales is incremental concept compared to the total sales. The percentage of positive commet tags ($Positive_{i,t}$) means that the proportion of the number of products *i*'s positive comment lags to that of total comment lags up to week *t* [We neglect the negative comments tags in this paper because the positive tags' ratio is highly correlated with the negative ones]. Unlike previous literature who regared five stars (or four stars) as positive comments and one stars (or two stars) as negative ones, this paper use the ratio of positive comment tags to measure the dgree of positive evaluation level. The reason why we choose this variable is that our data comes from Tmall, among which the red ones means positive tags and the green ones says the negative tags [Tmall will analyze each comments by text mining. When the system finds the contents contain a tag, this tag's number will plus 1. Consumers can view the summary information about all the tags in panel called "Cumulative Evaluation" directly]. The text mining technology help Tmall analyze the comments more deeply and provide the consumers with more precise information about the product relative to most B2C platform through out the world, who use just a few "stars" to measure the property of products.

"Description Accordance" ($Depict_{i,t}$) expresses the consistency between product *i*'s description in sellers page and the reality in week *t* and the percentage to average level in the same industry. The calculation rules: (the score of seller's store-the average score of the same industry)/(the highest score of the same industry –the average score of the same industry). "Refund Rate" ($Refund_{i,t}$) means the absolute value of seller's return rate of product *i* in week *t* relative to the average rate of the same industry. The calculation rules: seller store refund rate - the same average refund rate in the same industry(unit: day).

Figure 1 Various Comments Tags about a Notebook in Tmall

As mentioned above, we choose Ln_volume and $Positive$ as proxy for comments based WOM while $Depict$ and $Refund$ as proxy for e-SQ based online OL information.

Statistical Description and Corelation Analysis

Similar to chapter 5, we use the log form of weekly sales and the change of comments [For simplicity, we will describe the logarithm of weekly product sales as "weekly product sales" and the logarithm of the change of comments as "the change of comments"] because product sales comply with the law of diminishing marginal. In general, the product sales will increase rapidly early after the product was shown on the shelves and the increase rate will gradually slow down as time goes by. For the same reason, the change of comments will also agree with the law of diminishing marginal. We also notice that Refund in the data sample have a large skewness and kurtosis [For the original refund data, the skewness is 20.35, kurtosis: 648.52] which comes from the fact that the "refund" speed of few sellers deviate greatly from the mean, even Inconsistent with common sense (such as: "refund" speed is 78.2 days slower than the average). In order to ensure the sample data is a balanced panel, we make all the refund values in the quantile interval of 1%~99%. That means the refund values in the quantile interval of 0-1% will be given the value of quantile at 1% and the values in the quantile interval of 99%~100% will be given the value of quantile at 99% [After the treatment, the skewness of refund is -0.520 and the kurtosis of refund is 2.623]. After the treatment, the descriptive statistics of all variables and correlation are shown in Table 1.

Table 1 The Descriptive Statistics and correlations of all variables

Variables	Mean	Std.	Min	Max	[1]	[2]	[3]	[4]	[5]
[1]Ln_wsales	0.622	1.012	0	6.819	1.000				
[2]Ln_volume	0.438	0.873	0	5.613	**0.879**	1.000			
[3]$Positive$	0.049	0.109	0	0.543	**0.547**	**0.540**	1.000		
[4]$Depict$	0.073	0.138	-0.028	0.448	0.037	0.040	0.029	1.000	
[5]$Refund$	-0.019	1.310	-2.890	2.020	0.063	0.060	0.027	0.072	1.000

Table 1 shows that comments based WOM (Ln_volume and$Positive$) and product sales are highly correlated and Ln_volume has a strong correlation with$Positive$. E-SQ based online OL information (Depict andRefund) is weekly correlated with product sales and the two OL variables also have a small correlation. In addition, WOM variables and online OL information variables are also weekly correlated [For simplicity, comments based WOM and WOM contain the same meaning and e-SQ, OL information, e-SQ based OL].

Methods

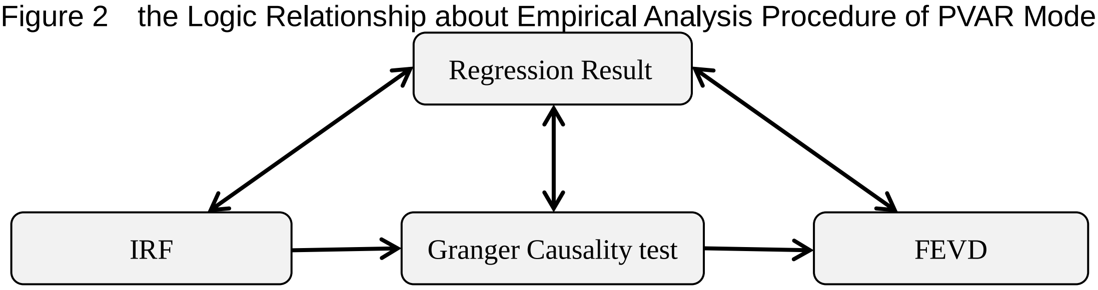
The purpose of this paper is to illustrate the dynamic interactions among product sales, comments based WOM and e-SQ based online OL information. The most appropriate method is Panel Vector Autoregression (PVAR) model since it can analyze dynamic interactions among endogenous variables. Time series based Vector Autoregression (VAR) model was proposed by Sims in 1980 and was extented to PVAR model by Holtz-Eakin et al. (1998) and then was developed and extented by Lütkepohl (2007). Now, PVAR have become a useful tool to study variables' dynamic interactions in panel analysis. PVAR model regards all the variables as endogenous variables [Actually, PVAR model can also analyze exogenous variables, but the model is mainly used to study the long-term dynamic interactions among several endogenous variables. So in most cases, exogenous variables are excluded in this model] and each endogenous variable are considered as the function of all the endogenous variables lagged term. This modeling approach reveals the long-term dynamic interactions among all the endogenous variables, the model as shown in equation (1). The model mainly employs the Impulse Response Function (IRF) and forecast Error Variance Decomposition (FEVD) as analysis tools. The former one is used to describe how the current one standard deviation impulse of the error term in one endogenous variable will impact on the trends of its own and other endogenous variables in the future periods. The latter one is used to assess the contribution of each endogenous variable that bear a standardized shock in the current period to the volatility forecasts in the future periods of all the endogenous variables in the system.

$$y_{i,t} = AY_{i,t-n} + Bx_{it} + u_i + f_t + \varepsilon_{it} \qquad (1)$$

Where, $y_{i,t} = (Ln_wsales_{i,t}, Ln_volume_{i,t}, Positive_{i,t}, Depict_{i,t}, Refund_{i,t})'$is the vector of endogenous variables, $Y_{i,t-n} = (y'_{i,t-1}, y'_{i,t-2}, \cdots, y'_{i,t-n})'$ is a $1\times 5n$ vector [The optimal lag order n of the PVAR model will be determined by the Information Criterion in section 4.2] of all the endogenous variables lagged from 1 period to n periods. A is a $5\times 5\mathrm{n}$ matrix that consisted by the coefficients to be estimated. x_{it} is exogenous variable. This study do not include exogenous variable and all the variables will be treated as endogenous. u_i is individual effect and it is used to reflect individual differences that cannot be observed directly (such as quality, brand and so on). f_t is time effect and it is used to capture the common shocks of all the individuals at the same time (such as "double 11" promotion). ε_{it} is the error term that subjects to normal distribution.

The rest of the paper will be organized as followed. At first, we will apply System Generalized Method of Moments (SGMM) to estimate the parameters of PVAR model, in which we will clarify which lag term of product sales, comment based WOM and e-SQ based online OL information have significant impact on the current variation of the three kinds of variables. Secondly, we will study the three kinds of variables moving trends in the future periods qualitatively if they suffer one standard deviation shock in the current period using IRF. And then, we will do Granger Causality test for the three variables to verify whether they have significant forecasting power between each other. Finally, we will illustrate how the current fluctuations of the three variables forecast their future variations that are a quantitative perspective evaluation about the forecasting power of one variable's variation on the other's variation, by FEVD. The empirical analysis procedure is shown in Figure 2. Along the procedure, the depth of analysis is increasing and they are logically related to each other [More information in section 3.5 and the first paragraph of section 3.6]. The relationship among the regression results and the three analysis method (IRF, Granger Causality test and FEVD) can be summarized as followed. Generally speaking, if the lag term of variable A have significant impact on variables B, the current shock in A will influence B in the future periods significantly in IRF analysis, A will be the Granger Causality of B in Granger Causality test and the variation of A Have a strong ability to predict the variation of B in FEVD analysis. The empirical results of this paper are consistent with the rules.

Figure 2 the Logic Relationship about Empirical Analysis Procedure of PVAR Model



EMPIRICAL RESULTS and ANALYSIS

Stationarity Analysis for Panel Data

Non-stationary time series data means that any past shocks will permanently change the series pattern in the future which may lead to t-test failure and spurious regression (or pseudo related phenomena). Panel data is a sepcial kind of time series data and we need to test the stationary property of all the related variables before regression. In practice, researchers usually use unit root test such as Levin-Lin-Chu test (LLC), Harris-Tzavalis test (HT), Breitung test, Im-Pesaran-Shin test (IPS), Fisher Augmented Dickey-Fuller test (Fisher ADF). The five tests share the same null-hypothesis, that is unit root exists in all the variables of the panel data (non-stationary) [The first four test assume that all the variables in the panel share the same autoregression coefficient while Fisher ADF assumes that each individual has different autoregression coefficient]. The stationary tests for the five key variables in this study are shown in Table 2.

Table 2 the Unit Root Test for all the Variables in PVAR Model

Null-hypothesis	methods	Ln_wsales	Ln_volume	$Positive$	$Depict$	$Refund$
H_0 : unit	LLC	-22.4738^{***}	-18.2709^{***}	-28.1793^{***}	-14.2187^{***}	-3.8583^{***}
	HT	-44.7098^{***}	-28.0549^{***}	-4.3300^{***}	-2.0007^{**}	-15.7275^{***}

root exist in all the variables	Breitung	-7.6231***	-9.4347***	-3.5587***	-2.1763**	-11.9329***
	IPS	-20.2118***	-16.9324***	-6.4998***	**15.9903**	-12.7599***
	FisherADF	-22.5821***	-22.3656***	-39.1667***	-3.5586***	-26.2894***

（Note: *** p<0.01, ** p<0.05, * p<0.1）

Table 2 shows that nearly [All the test reject the null-hypothesis under 5% significance except that IPS cannot reject the null-hypothesis of "Description Accodance" (Depict). Considering the practical meaning, we don't conduct differential treatment on the variables] all the test reject that the five variables (product sales, the change of comments, positive ratio of tags, "Description Accordance", "Refund Rate") have unit root. That is to say all the variables related to all study is stationary.

Choosing the Lag Order for PVAR Model

We need to determine the optimal lag oreder before parameter estimation and variable forecast using PVAR model. In this study, we will use AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), HQIC (Hannan-Quinn Information Criterion) to get the optimal lag oreder [Information criterion is used to describe the degree of information loss between a model and the "true model". The smaller one information criterion is, the better the corresponding model is]. The results are shown in Table 3.

Table 3 Information Criterion for PVAR Model

Lag Order	AIC	BIC	HQIC
1	-4.9431	**-3.1921***	-4.3176
2	-5.0634	-3.1798	-4.3886
3	**-5.1741***	-3.1435	**-4.4444***

(Note: * stand for the optimal lag order under different information criterion)

Table 3 indicates that these three kinds of information criterion for the optimal lag order haven't formed a consistent conlusion. There some differences among the three test such as: BIC/HQIC tend to choose simpler model while AIC tends to choose more "plump" model. However, BIC/HQIC is always better than AIC under normal circumstances. In this study we choose one lag order model, which is more concise and ensure the estimation results can be better explained.

Regression Analysis

SGMM estimation method is often used in PVAR model, in which the endogenous variables' lag term is used as instrumental variables for the regression equation. Nervertheless, the conventional method for eliminating time effect and individual effect is Within-Group Mean Difference (or mean difference method). This method will induce SGMM estimation failure as the lag term of endogenous variables will correlated with random error term which will result in instrumental variable failure. In order to overcome this problem, Arellano and Bover (1995) proposed a "forward mean-differencing" method (also known as Helmert process) to eliminate the forward individual mean [Before we use "forward mean-differencing" method, conventional mean-differencing method is used for eliminating the time fixed effect]. In this way, the lag term of endogenous variables and transformed error term are irrelevant from each other. Thus, SGMM estimation can also get effective results [Our analysis method is based on the Stata command pvar, written by Dr. Lian Yujun and Dr. Love. In this study, we modified the command pvar to pvar2 and get the regression results] as shown in Table 4.

Table 4 the estimation results for PVAR model

Current	$Ln\_wsales_{i,t}$	$Ln\_volume_{i,t}$	$Positive_{i,t}$	$Depict_{i,t}$	$Refund_{i,t}$

Lag term \ term	Estimateon	T-value	Estimat-eon	T-value	Estimat-eon	T-value	Estimat-eon	T-value	Estimat-eion	T-value
$Ln\_wsales_{i,t-1}$	**0.538*****	7.04	**0.207*****	4.28	**0.003****	2.12	0.000	0.17	0.024	0.46
$Ln\_volume_{i,t-1}$	**0.259*****	5.01	**0.338*****	8.84	0.001	1.08	0.000	0.09	-0.050	-1.46
$Positive_{i,t-1}$	**5.918****	2.28	-2.491	-1.51	**0.882*****	17.69	0.035	0.48	0.010	0.00
$Depict_{i,t-1}$	**0.854*****	2.91	0.075	0.40	0.001	0.08	**0.909*****	52.19	0.483	1.20
$Refund_{i,t-1}$	-0.010	-0.97	0.010	1.54	0.000	0.45	0.001	0.76	**0.736*****	31.05

（Note: *** p<0.01, ** p<0.05, * p<0.1）

In this paper, we will focus on four kinds of dynamic interactions, which derived from the analysis procedure of Villanueva (2008). The four interactions are summarized as followed. (1) the Reinforcement Effects among product sales, WOM and e-SQ based online OL information. Namely, we will discuss whether the lag terms of the three kinds of variables have impact on their current value. (2) the Direct Effects of WOM and e-SQ based online OL information on product sales. That is to say, we will evaluate the impact of the lag terms of WOM and e-SQ based online OL information variables on sales product. (3) the Feedback Effects of product sales, that is the impact of the lag terms of product sales on the current value of WOM and e-SQ based online OL information variables. (4) the Cross Effects between WOM and e-SQ based online OL information. Namely, we will study how will the lag terms of WOM variables impact e-SQ based online OL information variables and vice versa.

As illustrated in Table 4, we can get the following four conclusions. (1) On the whole, the first order lagged terms of all the variables have significant effect on themselves, which indicates that strengthening effect exist among product sales, WOM and e-SQ based OL information. (2) the first order lagged terms of the change of comments (log) and the percentage of positive tags have positive significant effect on the current state of product sales (log), consistent with most relevant studies such as Chevalier and Mayzlin (2006) [In their study the aggregate comments (lag) corresponds to the change of comments (log) and the percentage of “five star” comments corresponds to the percentage of positive comment tags]. The first order lagged term of “Description Accordance” has significant positive effect on the current state of product sales (log) while the first order lagged term of “Refund Rate” has no significant effect on the current state of product sales (log). This results indicate that whether the description on product sales page comply with the reality has a great influence on the potential purchasing decisions while consumers are not sensitive to the refund speed. This means that the two kinds of WOM variables and “Description Accordance” variable, one of online OL information variables, have a direct effect on product sales while the other variable of online OL information, “Refund Rate”, has no direct effect on product sales. (3) The first order lagged term of weekly product sales (log) has significant impact on the current state of the change of comments (log) and the percentage of positive tags [Lu et al. (2013) fond that the first order lagged term of sales had significant effect on the number of comments in restaurant which is consistent with our results] but has no significant effect on the current state of “Description Accordance” and “Refund Rate”, which indicate that product sales have feedback effect on WOM and have no effect on e-SQ based online OL information. (4) Neither the first order lagged term of two kinds of WOM variables nor the first order lagged term of e-SQ based online OL information variables have significant impact on the current state of each other. In addition, the first order lagged term of the change of comments (or the percentage of positive tags) has no significant effect on the current state of percentage of positive tags (or the change of comments) and the first order lagged term of “Description Accordance” (or “Refund Rate”) has no significant impact on current state of “Refund Rate” (or “Description Accordance”). This means that no cross effect exist not only among WOM variables and e-SQ based online information variables but also between two kinds of variables of WOM (or e-SQ based online information).

IRF Analysis

IRF analysis begins with the error term of one equation in the PVAR system got one standard deviation shock, under the condition that the current and past state of all the other variables unchanged, and then detect the future moving trends of all the endogenous variables [IRF analysis uses Choleski decomposition process, namely orthogonal decomposition is applied to the standard deviation impact of the error term, to generate the IRF, through which all the endogenous variables are required to be ranked by some rules and some hypothesizes about the endogenous relationships are made that the variable ranked near the frond has the effect on the current and lagged term of variables ranked behind it while the latter variable only has impact on the lagged term of the former variables. This means that the front position variable has stronger exogeneity than that ranked later (Liyan Han and Jing Lou, 2010)]. This kind of method can describe the interaction between variables visually. In this study, we applied the Monte Carlo simulation 1000 times and got the IRF diagram as shown in Figure 3 in which the horizontal axis represents the response periods (the unit is week and the maximum periods is 10 weeks) and the vertical axis represents the response of different endogenous variables that react to the impact. In the picture, we also present the 95% confidence interval for the response and the middle line in each small diagram indicates the trend of specific shocks.

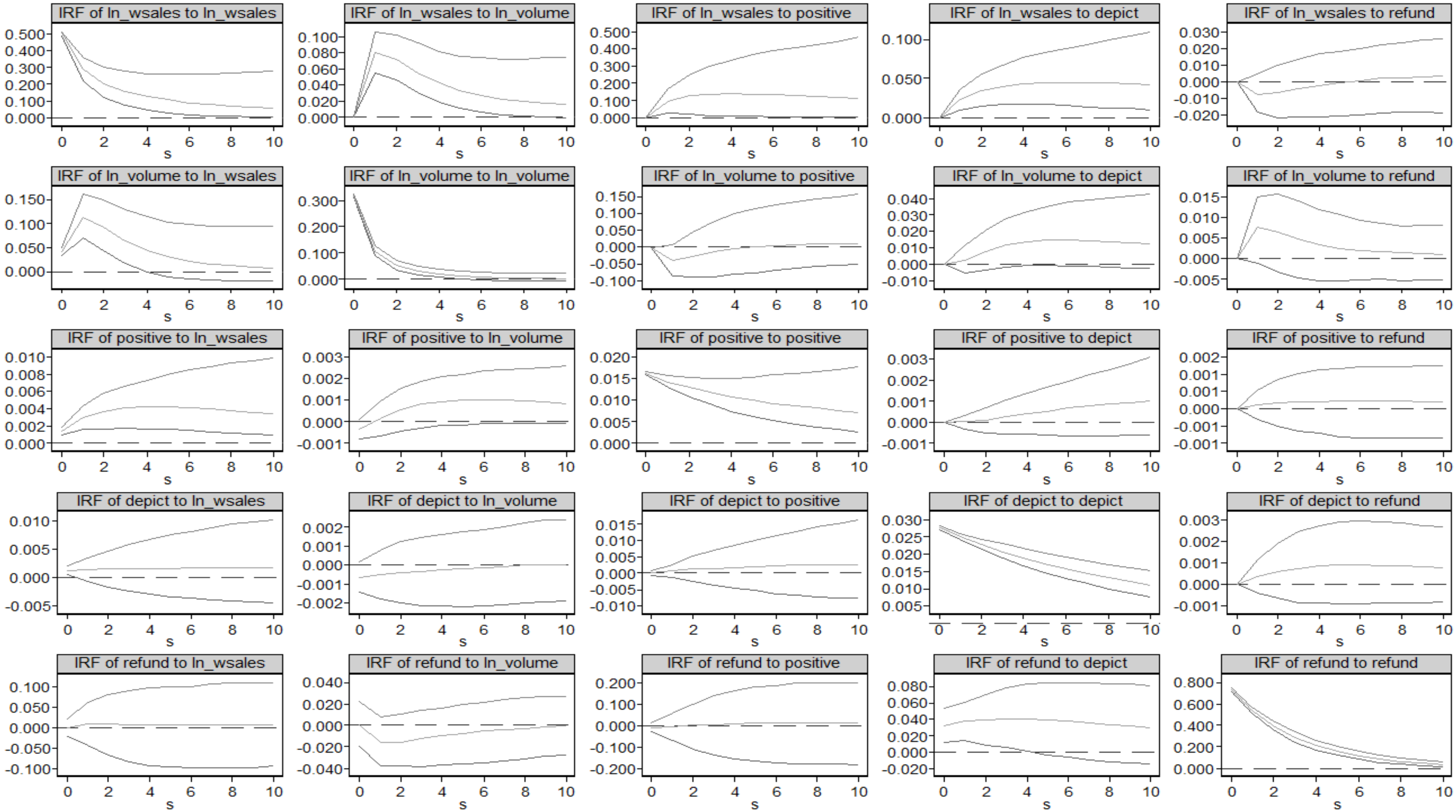


Figure 3　the IRF diagram of product weekly sales, comment based WOM and e-SQ based online OL information

Product weekly sales forecasting has shocks. As illustrated in the first line of Figure 3, as time goes by, the impact that product weekly sales have on itself decreases gradually but with a large value relatively. This means that the prediction of product sales is mainly due to itself. The change of comments has the greatest impact on the prediction of product weekly sales at the first week. The impact gradually decreased to 0 from sixth weeks, which indicates that the impact that the change of comments has on the prediction of product weekly sales weakened gradually with time. The impact that the percentage of positive tags have on the prediction of product weekly sales tends to be stable from the second week and maintains at a high level which means that the positive tags play a very important role in forecasting product sales. The impact that “Description Accordance” online OL information has on product weekly sales increases rapidly from the first four weeks and then slows down but the value is relatively small. The impact of “Refund Rate” is negligible relative to the factors analyzed above.

WOM prediction shocks. As shown in the second and third line of Figure 3, the impacts that the change of comments and the percentage of positive tags have on themselves reach the maximum in the current period and then the former decreases sharply and slows down after three weeks but the later decreases slowly at all the periods. Product weekly sales have the greatest impact on the change of comments at the first week and then the impact decreases gradually and become more flat after six weeks. The impact faced by the percentage of positive tags from product weekly sales increases gradually from the first week to the fourth week and then slowed down after four weeks. The impact that the percentage of positive tags have on the change of comments is negligible. On the contrary, the reverse impact increases gradually from the first week to the fourth week and then become more flat after four weeks with a relative small value. The impact that “Description Accordance” online OL information has on the change of comments resemble that of the percentage of positive tags. The impact that “Refund Rate” online OL information has on the change of comments reaches the maximum at the first week and then gradually decreased to 0. The impact that “Description Accordance” and “Refund Rate” online OL information has on the percentage of positive tags are negligible.

The e-SQ based online OL information shocks. As we can see from the fourth line and the fifth line, the impact that “Description Accordance” and “Refund Rate” have on themselves reach the maximum in the current period and decreased gradually. The impact that “Refund Rate” has on “Description Accordance” increases from the first week to the fourth week gradually and then tends to flat after four weeks while the reverse impact become flat from the first week. Product weekly sales have litter impact on e-SQ based OL information.

Panel Granger Causality Test

The analyses above have verified that the interaction exists among product weekly sales, WOM and e-SQ based online OL information. Nevertheless, the IRF can only describe the moving trends of the variables under the condition that one specific variable get a shock, which didn't reveal the causality relationships among the endogenous variables. At this section, Granger Causality test [Note: Granger Causality relationship is not the true causality relationship, it is a kind of dynamic relationship that reveals the "forecasting power" of one variable to another] is applied to answer this question. The result is shown in Table 5.

Table 5 Granger Causality Test for all the Endogenous Variables in PVAR Model

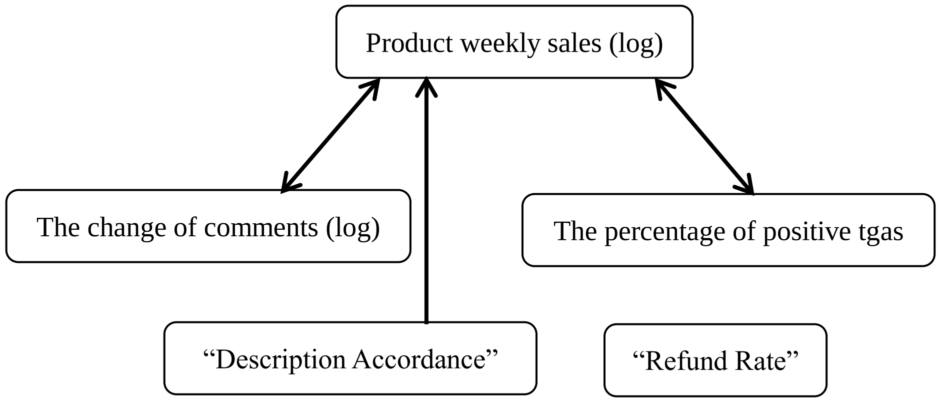
Granger Dependent Variables	Granger Independent Varables	H_0	χ^2	P
Weekly Sales(Log) （Ln_wsales）	Ln_volume	No	**25.118*****	0.000
	$Positive$	No	**5.2146****	0.022
	$Depict$	No	**8.4936*****	0.004
	$Refund$	No	0.9333	0.334
The change of comments (Log) (Ln_volume)	Ln_wsales	No	**18.33*****	0.000
	$Positive$	No	2.2799	0.131
	$Depict$	No	0.1622	0.687
	$Refund$	No	2.3768	0.123
The percentage of positive tags ($Positive$)	Ln_wsales	No	**4.5136****	0.034
	Ln_volume	No	1.1677	0.280
	$Depict$	No	0.0069	0.934
	$Refund$	No	0.1999	0.655
"Description Accordance" ($Depict$)	Ln_wsales	No	0.0301	0.862
	Ln_volume	No	0.0085	0.927
	$Positive$	No	0.2317	0.630
	$Refund$	No	0.5767	0.448
"Refund Rate" ($Refund$)	Ln_wsales	No	0.2143	0.643
	Ln_volume	No	2.1231	0.145
	$Positive$	No	0.0000	0.996
	$Depict$	No	1.4377	0.231

（Note: *** p<0.01, ** p<0.05, * p<0.1）

Table 5 shows that the change of comments (log), the percentage of positive tags, "Description Accordance" online OL information are Granger causal for product weekly sales (log). On the contrary, product weekly sales (log) is also Granger causal for the change of comments (log) and the percentage of positive tags but not for the two online OL information variables ("Description Accordance" and "Refund Rate"). In addition, neither the two variables of online WOM nor the two variables of online OL information have Granger Causality with each other and there is also no Granger Causality between WOM and online OL information. The Granger Causality relationships among the three kinds of variables are shown in Figure 4.

Figure 4 reveals that the Granger Causality relationships among the three kinds of variables are consistent with the results of PVAR estimation, i.e. (1)the change of comments (log) and the percentage of positive tags are reciprocal Granger Causality with product weekly sales (log) and in the regression results of PVAR, the first order lagged term of the change of comments (log) (or the percentage of positive tags) has significant impact on the current value of product weekly sales (log) but the converse is not significant. (2) “Description Accordance” online OL information is Granger Causality for product weekly sales but the converse is not, which is consistent with PVAR results that the first order lagged term of “Description Accordance” has significant impact on product weekly sales but the converse is not significant. (3) Granger Causality doesn’t exist between WOM and e-SQ based OL information, two kinds of WOM variables, e-SQ based OL information, “Refund Rate” and product weekly sales (log), in which the first order lagged term of one variable also has no significant impact on the other in the results of PVAR.

Figure 4 the Granger Causality Relationships among Product Weekly Sales, Online WOM and E-SQ Based Online OL Information



FEVD Analysis

Granger Causality test have revealed the causality relationships among product weekly sales, WOM, e-SQ based online OL information, which can also be interpreted as the “predicting power” of one variable to another. However, this test cannot determine the degree of the “predicting power”, namely, cannot reveal the degree of interaction between them. In order to study the interaction between them more precisely, this section will use FEVD to predict the fluctuations of every endogenous variable in future periods and the contribution of one standard deviation shock in current state of all the variables in the system and then evaluate the impact degree of one variable to another. The PVAR(5) system FEVD results are illustrated in table 6. As displayed in Table 6, we can get several conclusions as followed. When predicting product weekly sales, the greatest impact comes from itself in both shot-term and long-term prediction and the impact will decrease gradually from the first period to 20th period (from 100% to 62.9%). The impact of the shock in the change of comments (log) is small and is stable at around 3% in the fifth period. The impact of the shock in “Description Accordance” online OL information will increase slowly from the first period to 20th period but never exceed 4%. The impact of the shock in the percentage of positive tags will increase rapidly (from 0% to 30.6%). The shock in “Refund Rate” online OL information has no contribution to product weekly sales. This results indicate that the change of comments (log) and “Description Accordance” have some contribution to the future fluctuation of product weekly sales but with a week explanation power while the percentage of positive tags are more powerful in predicting the fluctuation of product weekly sales. This implies that the percentage of positive tags is an important reason for product sales and this impact has a long-term effect, such as: 30.6% of the forecasting variance of product weekly sales in the future 20th period can be explained by the percentage of positive tags.

Table 6 the FEVD Results for Each Endogenous Variable in PVAR Model

variables	Periods(week)	Ln_wsales	Ln_volume	$Positive$	$Depict$	$Refund$
	1	**1.000**	0.000	**0.000**	0.000	0.000
	5	**0.830**	0.033	**0.127**	0.010	0.000
Ln_wsales	10	**0.712**	0.030	**0.234**	0.024	0.000
	15	**0.657**	0.028	**0.282**	0.032	0.000
	20	**0.629**	0.027	**0.306**	0.038	0.000
	1	**0.017**	**0.983**	0.000	0.000	0.000
	5	**0.195**	**0.783**	0.019	0.003	0.001
Ln_volume	10	**0.203**	**0.767**	0.019	0.009	0.001
	15	**0.203**	**0.761**	0.022	0.013	0.001
	20	**0.203**	**0.758**	0.024	0.015	0.001
	1	**0.007**	0.000	**0.992**	0.000	0.000
	5	**0.063**	0.002	**0.935**	0.000	0.000
$Positive$	10	**0.097**	0.005	**0.896**	0.002	0.000
	15	**0.111**	0.006	**0.878**	0.005	0.000
	20	**0.117**	0.006	**0.868**	0.009	0.000
	1	0.002	0.001	0.000	**0.997**	0.000
	5	0.004	0.000	0.003	**0.992**	0.001
$Depict$	10	0.007	0.000	0.010	**0.982**	0.001
	15	0.009	0.000	0.018	**0.971**	0.002
	20	0.011	0.000	0.025	**0.961**	0.002
	1	0.000	0.000	0.000	0.002	**0.998**
	5	0.000	0.001	0.000	0.006	**0.992**
$Refund$	10	0.001	0.001	0.001	0.011	**0.986**
	15	0.001	0.001	0.002	0.014	**0.983**
	20	0.001	0.001	0.002	0.015	**0.981**

When forecasting the change of comments (log) (or percentage of positive tags), the largest impact comes from itself and will converge to 75%-77% (or 86%-90%) after 10 periods. Product weekly sales contribute a lot to it and the percentage of contributions maintained at 20.3% around (or 11% around) after 10 periods. “Description Accordance” online OL information have little impact to it and the ratio is 0.9% (or

0.2%) after 10 periods. The contribution of “Refund Rate” online OL information is almost 0. The forecasting power between the change of comments (log) and the percentage of positive tags is also not big. The later can explain 1.9%-2.4% for the future fluctuation of the former and the former can only explain 0.5%-0.6% for the later. This result indicates that the variation in product weekly sales is powerful in explaining the variation of online WOM while the variation in e-SQ based OL information has no explanation ability. In addition, the variations of the two variables in online WOM (the change of comments (log) and the percentage of positive tags) have week explanation ability for each other.

When predicting “Description Accordance” online OL information and “Refund Rate” online OL information, the future variation mostly comes from the shocks in themselves, which contribute 98.2% and 98.6% respectively to the variance forecasting of themselves in the 10th period. Product weekly sales (log) have little explanation ability to them and the ratio is 1.1% and 0 respectively in the 20th period. The contribution of the change of comments (log) is almost 0. The contribution of the percentage of positive tags increases gradually from the first period to the 20th period (from 0 to 2.5%) to the former while is almost 0 to the later. The forecasting power between the two variables of online OL information is also very weak. The later contributes nearly 0 to the former and the former can only explain 1.5% of the future variation for the later. This result indicates that neither the shock in product weekly sales nor the shock in online WOM has explanation power in predicting the future variation of e-SQ based online OL information. The future variation of e-SQ based online OL information variables depend on the shocks in themselves mainly and no strong explanation ability is found from one OL information variable to the other OL information variable.

CONCLUSIONS

This paper applied PVAR model to study the dynamic interaction among product weekly sales, online WOM and e-SQ based online OL information with the help of the largest B2C e-commerce platform in china, Tmall.com, which has rich data in its’ sales page. In addition, IRF, Granger Causality test and FEVD were used to analyze the mutual prediction among the three kinds of information. This method can describe the future moving trends of the variables under the current shock in one variable and analyze the forecasting power of the current variation in one variable to the fluctuation of all the variables. The results shows that: (1) Product weekly sales online WOM and e-SQ based online OL information have dynamic effect in themselves, that is their past performance have impact on the current performance significantly. There are dynamic interactions among all the variables in Product sales and online WOM (the change of comments and the percentage of positive tags). Product weekly sales and “Description Accordance” （one of the online OL information variables）only have one directional dynamic effect [The later have siginificant impact on the former while the former do not have siginificant impact on the later] and the other online OL information variable (“Refund Rate”) have no dynamic interaction with product weekly sales. (2) Apart from their own impact, the percentage of positive tags has strong explanation ability in prediction the fluctuation of product weekly sales (approaching 30% in the long run). The shock in product weekly sales perform best in explaining the fluctuation of online WOM (in the long run, the explanation ratio is 20 for the fluctuation of the change of comments and the ratio is nearly 12% for the percentage of positive tags). However, the contributions for e-SQ based online OL information variables mainly come from themselves (96% for “Description Accordance” and “98” for “Refund Rate” in the long run).

E-SQ based online OL information. At present, Tmall sellers haven’t engaged in improving the level of e-SQ performance according to the sales information especially for the description consistency in products introductions. If sellers present exaggerated or false description, the sales may increase in a short term but it is harmful to the long term revenue for the sellers as “Description Accordance” has a positive dynamic impact on product weekly sales significantly. So sellers should improve the e-SQ according to the sales information and sellers should also address more importance of description consistency.

The comment tags. Because the percentage of positive tags volatility can explain 30% of the fluctuation of product weekly sales, the amount of positive tags will impact the change of product sales greatly. As this reason, Tmall sellers should monitor the number of positive and negative tags timely and raise alarm on the negative comments from consumers. Sellers need respond and explain for the subjective and unfair negative comments to prevent these negative comments from prevailing among consumers. Nevertheless, if the negative comments are due to the defects of the products themselves, sellers should improve the quality of the products from the perspective of revenue and cost and then guide the consumers to write more positive comments on the website page.

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