A Dynamic Process of Two-Sided Customer Activity: Findings from B2B Electronic Market

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Abstract: The degree of two-sided users' participations are critical important for B2B electronic market makers. This research focuses on the role of the active degree of users behaviors. In the context of B2B electronic market, we examine the relationship of users' activity of two sides and platform performance with VAR model. Furthermore, we investigate how advertising strategies improve the active degree of user behaviors. The results show that the active users in different sides will play differently related to their short-term or long-term effect on the platform performance. Moreover, the authors find that the external customers which attracted by adverting (search advertising and event marketing in this paper) can significantly influence the internal participants' activity. These findings emphasize more exploration should be pay attention to the quantity of user base in two-sided markets, and provide guidance related to advertising strategy too.
Keywords: advertising strategy; active degree of participation; two-sided market; VAR.

1. Introduction

Nowadays 60 of the world's hundred excellent companies are benefit from the economics of two-sided networks (Eisenmann, Parker, and Alstyne 2006), these markets consist of a market maker (or platform) that manages the market and the participant firms— namely, buyers and sellers— that transact in it. Recent advances in electronic markets has made significant advances in the understanding of various marketing issues related to two-sided market, especially B2B electronic markets got substantial exploration as its prominent position in e-commerce (U.S. Census Bureau 2009). Most research dominantly focus on the role of market makers (Grewal, Chakravarty, and Saini 2010) and ownership structure (Yoo, Choudhary, and Mukhopadhyay 2007). Moreover, the impact of two-sided users' actions to stimulate the performance of platform is uncertain.

On the other hand, prior studies in this area are mostly on the perspective of user networks in two-sided markets (Basu, Mazumdar, and Raj 2003; Nair, Chintagunta, and Dubé 2004; Stremersch et al. 2007), these "quantity" emphasized literatures found that the network effect can contribute to the sizes of two-sided user bases. But, in recent tine, many researchers pointed out that we should pay more attentions to the role of the quality of two-sided users' behaviors (Binken and Stremersch 2009;

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Landsman and Stremersch 2011). Landsman and Stremersch(2011) examined the effect of seller-level multi-homing and platform-level multi-homing, but neglect the role of two-sided users' activities. The active degree of users' behaviors is an important characteristic of behavior quality, which can influence platform performance more directly. Firstly, the higher active degree of user behavior will enlarge their corresponding network effect (Wilson, Boe, Sala, Puttaswamy and Zhao 2009). Secondly, active users can improve the performance of the platform and foster a stronger competitive capability than competitors (McHugh and Larsen 2010). In this reason, we prefer to explore two research questions in this study: 1) The dynamic influence of two-sided customer activity on the performance of platform; 2) What will influence two-sided customer activity and their corresponding effect?

After collecting time series data from a B2B electronic platform lasting for a whole year, we used VAR model to explore prior two research questions. By analyzing the Impulse Response Functions (IRFs) results, the key results from our analysis for this B2B electronic platform are summarized below: (1) The active degree of sellers can enhance the platform performance more than the active degree of buyers, no matter short-term elasticity or long-term elasticity. (2) Advertising strategies (we use "AD strategy" as a shorter term, including search advertising and event marketing) would attract more potential users to stimulate the activities of two-sided users, and both AD strategies will motivate the buyers' activities more than the sellers' activities. (3) Search advertising can drive the active degree of buyers' behavior more than event advertising, but event advertising has larger effect on the active degree of seller behavior than search advertising. (4) The role of AD strategies on platform performance is not significant, their effectiveness are manifest through the role of active degree of two-sided users behaviors.

Our research tries to provide dynamic influence mechanism of two-sided user behavior, and discusses the relationship of AD strategies (try to attract potential users) and internal user behavior. This remainder of the paper is organized as follows. In section 2, we provide a brief review of the relevant literature on two-sided market, advertising strategies. In chapter 3, we present the detail of our VAR model including method and variables. In chapter 4, we present the data and discuss the analysis results we get. Finally, we conclude with an overview of findings, the managerial implications and theory contributions.

2. Theoretical Background

This paper is related to two streams of literature: research on two-sided market and online advertising strategy.

2.1 Two-sided Market

Two-sided markets refer to the markets in which one or several platforms enable interactions between end-users, and try to get the two sides "on board" by effectively marketing and management strategies (Rochet and Tirole 2006). Thus, the three main components in two-sided markets can be easily concluded are one platform and two user bases (sides).

In a two-sided market, the financial success of any platform company critically depends on its ability to actively attract and grow two kinds of participants: buyers and sellers. The two groups are attracted to each other–a phenomenon that economists call the network effect, including cross-side network and same-side network effects (Eisenmann, Parker, and Van Alstyne 2006). Cross-side network means through improving the scale of users on one side, the agents in the other side will be encouraged (Bucklin and Sismeiro 2003, Ellison and Ellison 2005), while same-side network effect means when increasing the size of one user base, members of the same side may be positively or negatively affected (Kurucu and Gokce 2007). Prior literatures have already documented the significant effect of user networks as they can create a unique “start-up” difficulty and “winner-take-all” market outcome (Wang, Chen, and Xie 2010).

In order to facilitate the network effect, scholars have investigated some strategies to motivate the activities of both users. Tucker and Zhang (2010) indicate that the platform company often advertises their number of users, presumably to encourage further participation. Parker and Van Alstyne (2005) use network effect to explain many free pricing strategies where one user group gets free use of the platform in order to attract the other user group. Moreover, there is no consensus related to which side of the market can contribute to the platform performance more effectively. Cross-side network externalities give rise to a "chicken & egg" problem (Caillaud and Jullien 2003). Fathand Sarvary (2003) find through analytical analysis that it is benefit to subsidize one group of users (i.e., buyers) to achieve critical mass so as to increase growth. But Bucklin and Simeiro (2003) and Ellison and Ellison (2005) find that the existence of many sellers is more likely to attract traffic of buyers. Actually, the behavior quality of both user should be get more attention (Landsman and Stremersch 2011), like the active degree of existing users. As most strategies can only influence active users more directly other than all users, and active users can play more effect on platform performance than inactive ones.

For the purpose of finding out the influence process of active sellers and active buyers, we incorporate this network effect into our analysis and examine how active buyers and sellers as well as their dynamic interactions, contribute to platform advertising revenue. To further investigate how to motivate the activities of both users, we incorporate advertising strategies to explore their roles on the active behaviors of sellers and buyers.

2.2 Advertising Strategies

The role of advertising strategies have been acknowledged and research in depth, they have direct effect on sales (Hanssens, Parsons, and Schultz 2001), and indirect effect on stock price (Steenkamp, and Fang, 2011) and firm value (Joshi and Hanssens, 2010).

This paper proposes to explore the effectiveness of advertising strategies on the active degree of users’ participation in B2B electronic market. AD strategies are valuable for existing buyers and sellers’ activities, because they can attract more potential users which can increase both the communication and transaction. Considering their target audiences maybe potential buyers or sellers, it’s still hard to distinguish how effective AD strategies can influence the behaviors of sellers/buyers, and eventually cause the fluctuations of platform performance in B2B electronic market receptively.

In this paper, we only pay attention to two typical AD strategies: search advertising and online event marketing. Search advertising, event marketing are two primary categories of advertising (Trusov, Bucklin and Pauwels 2009). The former one aims to pull new customers who try to find some information related to target platform firms, while the later one aims to push potential users to pay attention to the platform firms with some external stimulation. Search advertising allows companies to address consumers directly during their electronic search for products or services (Rutz, Bucklin and Sonnier 2010). Event marketing can attract more passers-by to have a deep knowledge of platform and specific service. But there is little research discussed their role on the platform performance, whether they can play directly or indirectly through the active behaviors of existing users. In summary, we conceptualize our research framework as Figure 1 and investigate their dynamic influence process.

[Insert Figure.1 about Here]

3. Model Specification

We adopt a Vector Autoregression (VAR) model to capture the interdependent evolution of the variables of platform performance. The evolution of each variable (the exploitation and exploration buyer/seller) is explained by the lag of itself and other variables. By treating each variable as potentially endogenous, the VAR model is particularly suitable to capture the dynamic and complex interdependence between the performance variables without making stringent identification assumptions. Based on the estimated VAR parameters, simulation techniques can be applied to derive the long term impact of a shock in one variable on all the other variables.

Our analysis follows the standard procedure of VAR modeling, which consists of the following steps: (1) we test for evolution or stationarity of all the variables in our study, perform unit-root tests, and conduct the Augmented-Dickey-Fuller (ADF) unit-root to test the null hypothesis of a unit root test by Ender (1995) and the Kwiatkowski-Phillips-Schmidt-Shin test (1992). (2) We found the variables to be stationary or evolving, in line with the empirical generalization described by Dekimpe and Hanssens (1995 “The persistence of marketing effects on sales”). We further test for the presence of cointegration, or long-term coevolution. (Table 1) (3) Depending on the outcome of these tests, the model is estimated in first-order difference. We should control deterministic components such as a base level (constant), a deterministic (time) trend, week and lags of the dependent variable (Box and Jenkins 1970; Trusov, Bucklin, and Pauwels 2009). (4) The estimated VAR models, with the appropriate lags (1-lags) determined by the AIC and Schwarz BIC (AIC= 91.64254, SC= 92.22698), showed a good fit. The above procedures are discussed in detail in Dekimpe and Hanssens (2004). Our final step (5) is deriving the Impulse Response Functions (IRFs). The IRFs trace the over-time impact of a unit shock in any endogenous variable on the other endogenous variables. Following Dekimpe and Hanssens (1999), we use generalized IRFs (or simultaneous shocking) to ensure that the ordering of variables in the system does not affect the results and also to account for contemporaneous or same-period effects. In the context of our research questions, we use impulse response functions to disentangle the short and the long-run effects of exploitation and exploration sells/buyers on the performance of platform. Given a VAR model in differences, the total shock effect at lag k is obtained by accumulating the lower-order IRFs. Following Dekimpe and Hanssens (1999), Nijs and colleagues (2001), Trusov, Bucklin, and Pauwels (2009) and Joshi and Hanssens(2010), we determine the duration of the shock (maximum lag k) as the last period in which the IRF value has a ｜t｜-statistic greater than 1.

[Insert Table.1 about Here]

We propose a five-variable VAR system to capture the dynamic interaction between the platform performance (PERFORM), active buyers (BUYER), active sellers (SELLER), search advertising (SEARCH), and event marketing (EVENT). The vectors of exogenous variables include for each endogenous variable (1) an intercept, C, and (2) a deterministic-trend variable, T, to capture the impact of omitted but gradually changing variables, and 3) indicators for days of the week, D. Instantaneous effects are captured by the variance–covariance matrix of the residuals, Σ.

$$
\begin{bmatrix} SEARCH_t \\ EVENT_t \\ SELLER_t \\ BUYER_t \\ PERFOM_t \end{bmatrix} = \begin{bmatrix} C_{SEARCH} \\ C_{EVENT} \\ C_{SELLER} \\ C_{BUYER} \\ C_{PERFORM} \end{bmatrix} + \begin{bmatrix} \delta_{SEARCH} \\ \delta_{EVENT} \\ \delta_{SELLER} \\ \delta_{BUYER} \\ \delta_{PERFORM} \end{bmatrix} \times \mathrm{T} + \begin{bmatrix} \gamma_{SEARCH} \\ \gamma_{EVENT} \\ \gamma_{SELLER} \\ \gamma_{BUYER} \\ \gamma_{PERFORM} \end{bmatrix} \times \mathrm{D}
$$

$$
(1) \quad + \sum_{j=1}^{J} \begin{bmatrix} \phi_{11}^j & \phi_{12}^j & \phi_{13}^j & \phi_{14}^j & \phi_{15}^j \\ \phi_{21}^j & \phi_{22}^j & \phi_{23}^j & \phi_{24}^j & \phi_{25}^j \\ \phi_{31}^j & \phi_{32}^j & \phi_{33}^j & \phi_{34}^j & \phi_{35}^j \\ \phi_{41}^j & \phi_{42}^j & \phi_{43}^j & \phi_{44}^j & \phi_{45}^j \\ \phi_{51}^j & \phi_{52}^j & \phi_{53}^j & \phi_{54}^j & \phi_{55}^j \end{bmatrix} + \begin{bmatrix} SEARCH_{t-j} \\ EVENT_{t-j} \\ SELLER_{t-j} \\ BUYER_{t-j} \\ PERFORM_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{SEARCH,t} \\ \varepsilon_{EVENT,t} \\ \varepsilon_{SELLER,t} \\ \varepsilon_{BUYER,t} \\ \varepsilon_{PERFORCE,t} \end{bmatrix}
$$

The VAR specification is given by where t indexes days, J equals the number of lags included (to be determined on the basis of the Akaike information criterion), D is the vector of day-of-week dummies, and ε are white-noise disturbances distributed as N(0, Σ). The parameters δ, θ, γ, and ϕ are the ones to be estimated. Because VAR model parameters are not interpretable on their own (Sims 1980), effect sizes and significance are determined through the analysis of impulse response functions (IRFs) and elasticities computed on the basis of the model.

4. Empirical Analysis

4.1 Sample

We collected data from a world famous electronic B2B platform, and it is the global leader in e-commerce for small business in various industries. This platform establishes offices in more than 70 cities across the United States, Europe, China, India, Japan, Korea, etc. As part of its strategy to transition into a holistic platform where small companies can find their potential traders more easily, it invests in advertising in many portals and engines (like Yahoo! and Google). Event marketing also have been taken since 2008, in which platform itself or cooperate with other complementary firms to attract potential users by establishing some conjoint marketing activities like charity or business knowledge training.

4.2 Data Description

By modeling the composite active buyers' and sellers' response towards ads, we aggregate (1) search advertising as the new members who click ads due to the links of search engine outside the platform; (2)event marketing exploitation as the incumbent participants who come from the link form the complementary website; (3)active sellers exploration as the magnitude of the ones who offer products on the platform; (4)active buyers exploitation as the magnitude of the buyers who give feedback via customer service without offering any trading goods. Finally, we aggregate platform performance exploitation as amount of platform revenue. Table 2 provides an overview of the operationalization of our variables.

[Insert Table.2 about Here]

In order to capture the long-term relationship between advertising and platform performance and reduce the time-variant effect, we collected data from March 31st in 2008 to March 31st in 2009 on a daily basis, altogether 366 valid items. And their descriptive information is as follows, see in Table 3.

[Insert Table.3 about Here]

5. Results

To gauge both short-term and long-term interactive relationship among the active degree of user behavior, advertising and the platform performance, we compute IRFs up to 4-week lags on the basis of the estimated VAR system parameters. First, the IRFs trace the incremental effect of a one-standard-deviation shock in active buyers and active sellers on the platform performance (see Figure 2.). Second, we examine the carryover effects of search advertising and event marketing on active sellers and buyers respectively in a dynamic system (see Figure 3.). Finally, we measure the direct impact of advertising on the platform performance (see Figure 4.), and collect the vital information of these IRFs in Table 4 and Table 5.

5.1 Quality of User Bases Effect on the Platform Performance

The impact of the active degree of sellers on the platform performance is found to be significant and bigger than buyers' through all the period. In the short run, the active sellers have positive effect on the platform performance, while in the long run it turns to be a negative one (since 7 days). On the other side, the active degree of buyer behavior insignificantly affects the platform performance in short-term, and then creates a positive effect after approximate 3 days.

These differences show that, an activity degree of sellers change will firstly motivate users to get addition paid service from the platform which is the main component of performance. Later, the fierce competition brought by amount of sellers will do harm to the successful transaction rate and the confidence of users. However, the active degree of buyers would increase the transactional opportunities only after an observation period (about 3 day) instead of an immediate raise.

[Insert Figure.2 about Here]

5.2 Advertising Effect on Quality of User Bases

Various advertising methods are documented to have different on quality of user behaviors in two sides (see Figure 3). On the one hand, both search advertising and event marketing can significantly influence the active degree of seller behavior in long-term (after 14 day). Comparing the various kinds of advertising in the long run (14 day), the elasticity of event marketing (.01892) is 27 times higher than that of search advertising (.00705). But in short-term, search advertising has no significant effect at all. On the other hand, event marketing has a short-term effect, but this short-term effect does not directly translate into long-term behavior, while the search advertising has both the short-term and long-term effect on the active degree of buyer behaviors.

These results indicate that advertising (search advertising and event marketing) can effectively motivate the active degree of two user bases. New comers from search adverting with more accurate objective can immediately incent buyers to consume on the platform, while sellers always need time to predict or make decisions. However, event marketing cause a simultaneously response by buyers, but such response to events does not last for a long time. Because compared with sellers, buyers do not need to operate their business and they only focus on the products or services they want for the period of making decision.

[Insert Figure.3 about Here]

5 .3 Advertising Effect on the Platform Performance

According to the result of IRFs (see Figure 4), there is non-significant direct effect of advertising on the platform performance, thus our empirical findings support the notion that advertising may affect the platform performance in an indirect way through a process (such as affect active sellers and active buyers firstly). The innocent participants from the advertising can not lead users to pursue the advanced service and information by paying for platform, but they can motivate the existing buyers or sellers to improve the platform performance. We get the conclusion that advertising strategy affects platform performance by incenting the user behaviors.

[Insert Figure.4 about Here]

[Insert Table.4 about Here]

[Insert Table.5 about Here]

6. Discussion

Despite the high relevance of advertising strategy in two-sided market, the mechanism of the various advertising and its effect on the platform performance on the view of active users have received little empirical attention from academics. In the current study, we address this gap theoretically and empirically. We adopt VAR model to capture the effects of the advertising on the two-sided market performance, and take the active degree of user behavior as an important role in this mechanism.

In this section, we summarize our main findings and then discuss our theoretical and practical contributions. We conclude with a discussion of the limitations of the current study and the directions for the further research.

6.1 Summary of Findings

We find that the active degree of user behaviors can directly affect platform performance. In short run, the active sellers have positive effect, while in long run (after 7 days) it turns to have negative one. To the active buyers, the short-term effect (the current day) can’t be proved, but it can actually increase the platform revenue in long run (after 3 days). However, thus far, prior researches on advertising in two-sided markets have focused exclusively on the direct effect on the sales or performance. We also find that that there is no direct relationship between them but advertising can improve the active degree of user behavior, then the active participants will enlarge the platform performance.

Moreover, we find that different advertising strategies like search advertising (pull strategy) and event marketing (push strategy) we mentioned in this paper can influence users in different ways. On the one hand, search advertising drives the extent of active-level behavior in both sides for a long term (after 14 days), while is not significant in the short run (the current day) for sellers. On the other hand, event marketing drives active-level behavior in both sides for a short term with larger elasticity compared with search advertising, while not significant in the long run (after 3 days) to buyers.

6.2 Implication for Marketing Theory

Existing research have emphasized the user quantity in depth (Basu, Mazumdar, and Raj 2003; Nair, Chintagunta, and Dubé 2004; Stremersch et al. 2007), while this paper investigates on the perspective of user quality (about user behavior). So the first theoretical contribution of this study is that we document the two-sided users’ quality (like the active degree of two-sided customers in this paper) can significantly affect the platform performance but in a dynamic way. Scholars should also pay attention to these differences, especially the long-term negative effect of active degree of sellers.

Secondly, these conclusions enrich the literatures on the relationship of advertising and user behaviors, while also reflect the dynamic influence mechanism between the activity of external users and internal users. Advertising attracts innocent comers as external ones, which can offer both the competition and opportunities for transactions, and incite the existing users as internal ones in both sides. In this paper, we choose two dominant strategies: search advertising (pull strategy) and event marketing (push strategy). Comparing with WOM (world of mouth) strategy, they can easily be controlled by platform managers, and also have significant effects on the user behavior (active degree). For buyers, the pull strategy works all the time, while the push one can only last for short days (less than 3 day). And for sellers, the pull strategy only act after an observation period (maybe 14 days), comparing with the push one can perform constantly.

Finally, these findings shed light on some documented ambiguities surrounding the advertising mechanism on performance in two-sided market. Although the prior studies have not demonstrated the direct relationship between advertising strategy and platform performance, we find an indirect way instead. Advertising can influence platform performance by incite the two-sided user behaviors firstly, which means different advertising strategy can promote two sides users' behavior to make them more active, then the active users can actually increase the performance finally.

6.3 Managerial Implications

For managers of mature platforms, the preceding conclusions may explain why the investment of advertising can not directly improve the revenue, a phenomenon seemingly at odds under different circumstance. The core reason mentioned in this paper is the important role of the active degree of user behaviors (both seller and buyer), which is the main factor works in direct way. As we noted previously, increase the activity of buyer can benefit the performance for a long term, while the activity of sellers would improve the performance in short run, and reduce it in long run. So platform administrators can make decisions of incitement strategy for users according to their own target.

Our research findings also have substantial implications for the method to encourage the user to be active, and finally increase the platform performance. Advertising strategy like search advertising and event marketing are both effective way. Event marketing is helpful for short-term performance via the way of increasing seller activity, while search advertising is suitable for long-term performance via the way of increasing buyer activity. So the platform makers should value the advertising strategy even it does not work directly.

6.4 Limits and Further Direction

There are several ways to extend this research. First, in the market setting we study, we only focus on the active participants, but it would be vary interesting to investigate the value of silence users. Because silence users also can contribute to the scale of bases, a signal for the superior value of platform (Schilling, 1999; Landsman and Stremersch, 2011). Moreover, the inactive participators can be encouraged to be active ones via proper advertising strategies, while the positive consumers may turn to be negative one through evolution themselves. So the life time of consumers is worth to explore in the new context like two-sided market (Chan, Tat Y., Wu, Chunhua, Xie Ying 2011).

Second, as our model only present the exploration of advertising mechanism in the context of mature two-sided market, but it may not apply for the new one or with small market share. It would also important to document the mechanism in various contexts like the SNS platform or online community in which the active degree is more critical.

Finally, the crucial role of active degree of user behavior can be an important topic and deserves full analytical exploration. It would also be useful to further explore the imputation under uncertainty effect. Both the participant and platform uncertainty can moderate the relationship between active degree and advertising strategy. Most importantly, further empirical and theoretical research should move beyond the influence of the mere network size in the analysis of two-sided markets, and focus more on the quality of the network bases.

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APPEBDIX

FINGER 1
Research Model

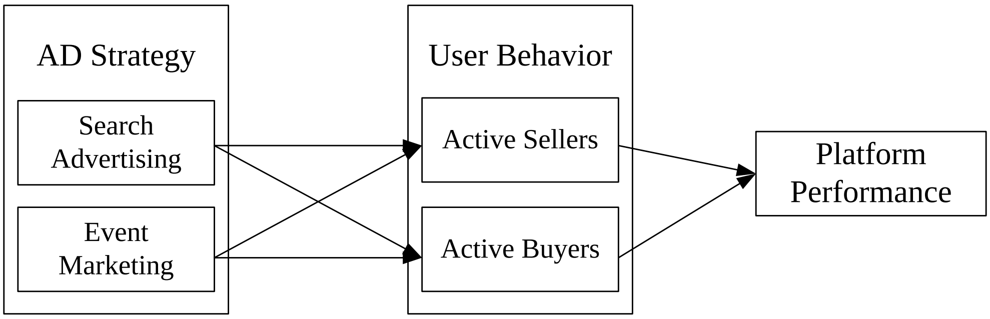


FIGURE 2
IRFs: Response of Performance in Active Seller and Buyer

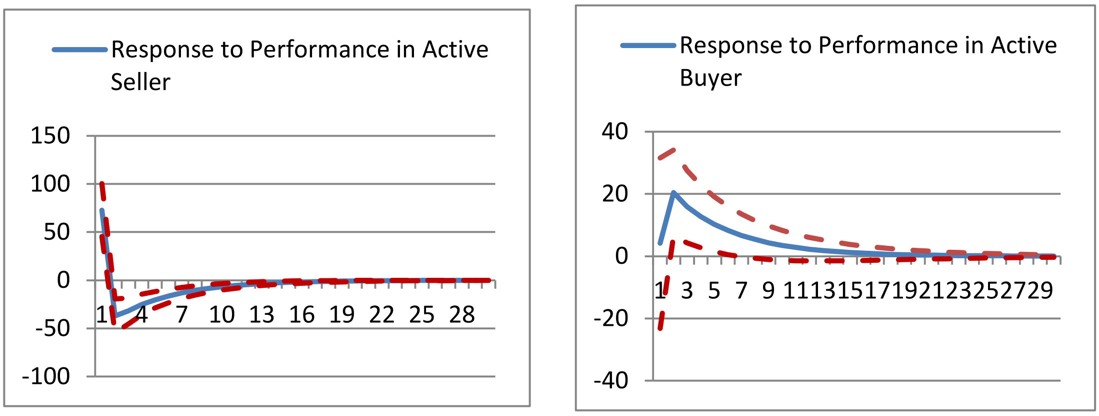


FIGURE3

IRFs: Response of Active Seller and Buyer in Advertising

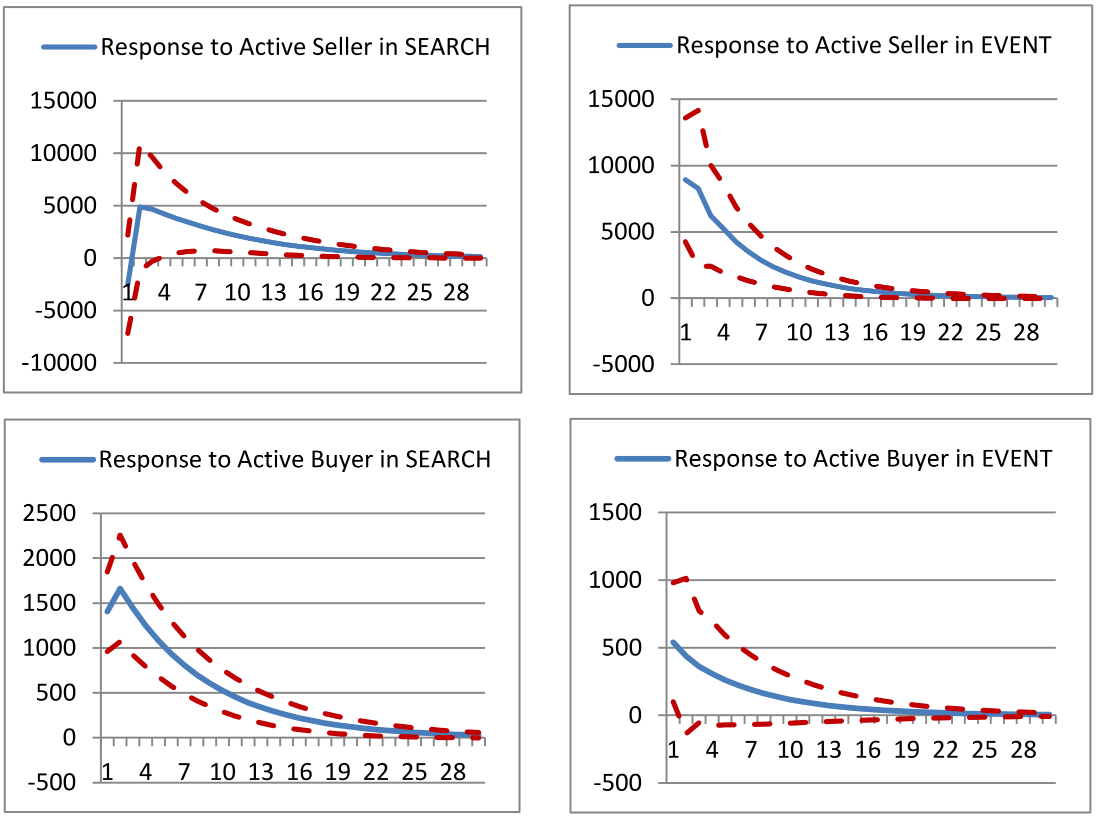
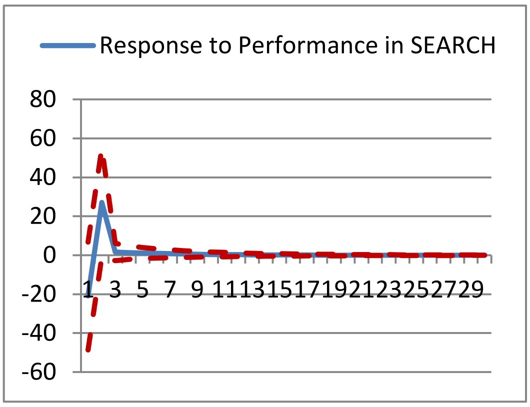


FIGURE4

IRFs: Response of Performance in Advertising



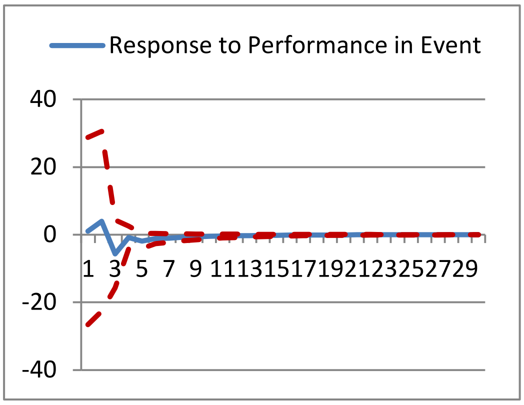


TABLE1

UNIT ROOT TEST AND MODEL FIT RESULTS

Variable	t-value
Search Advertising (SEARCH)	-2.53(in level) -4.76***(in change) [a]
Event Marketing (EVENT)	-1.38(in level) -9.14***(in change)
Active Sellers (SELLER)	-6.32*** (in level)
Active Buyers (BUYER)	-5.34***(in level)
Platform Performance (PERFORM)	-1.08 (in level) -4.12***(in change)

*: p<0.1, **: p<0.05, ***: p<0.001; a: test for unit root in 1st difference.

TABLE2

VARIABLE OPERATIONALIZATION

Variable	Type	Operationalization
SEARCH (search advertising)	Endogenous	The daily number of new members who land website due to search engine advertising and click ads after they search in this website. Characteristics: (1) no existing user account, but his IP can be identified; (2) login this website due to search engine advertising; (3) click ads.
EVENT (event marketing)	Endogenous	The daily number of innocent participants who search and click ads due to the links of some complementary firms' website. Characteristics: (1) sharing user account with other firms and his IP can be identified; (2) login this website due to

		the cooperative firms or event pages; (3) click ads.
SELLER (active sellers)	Endogenous	The daily number of active sellers who participate in offering products in recent with transaction record. Characteristics: (1) own an existing seller account, register his account in the recording day; (2) participate actively in transaction according to transaction records.
BUYER (active buyers)	Endogenous	The daily number of active buyers who give feedback via platform system without any offers since registered. Characteristics: (1) own an existing buyer account, and his account was registered before the recording day; (2) participate actively in transaction according to the feedback records.
PERFORM	Endogenous	The revenue of the platform.
T	Exogenous	Time trend
D	Exogenous	Indicators for days of the week (using Friday as the benchmark)

TABLE3

Descriptive Statistics (Daily Data)

	Num	Mean	Maximum	Minimum	Mdn	S.D.
SEARCH	366	2876.047	5021	506	2795.5	788.4644
EVENT	366	4629.349	9683	0	5149.5	2315.218
SELLER	366	419002.0	718264	36410	432685	150501.3
BUYER	366	23649.55	145278	1346	22278	17339.79
PERFORM	366	339447.8	393776	277546	345860	31048.68

TABLE4

Result of IRF to performance

Period		SELLER	BUYER
Short-term effect	elasticity	3.26305	0.01067
	t-value	-2.64578	-0.15329
Long-term effect	elasticity	1.325287	0.07641
	t-value	-1.074585	-1.09773
	duration	7	3

TABLE5

Result of IRF to SELLER and BUYER

Period		SELLER		BUYER	
		SEARCH	EVENT	SEARCH	EVENT
Short-term	elasticity	0.003673	0.01314	0.3856	0.24013

effect	t-value	0.534059	-1.91018	-3.16492	-1.22541
Long-term effect	elasticity	0.00705	0.01892	0.35632	0.19618
	t-value	-1.02537	-1.71072	-2.92459	-0.95939
	duration	14	7	7	3