Summer 5-27-2016

Game Analysis on Credit Supply of Online Shopping Platform

Tu Jing
School of Management, Wuhan University of Science and Technology, China

Game Analysis on Credit Supply of Online Shopping Platform

TU Jing
School of Management, Wuhan University of Science and Technology, China

Abstract: With more internet giants develop online shopping platform, the credit of platform has become the key point of competitive advantages. The sellers are the supplier of credit, while the platform is the supervisor of credit. Game model is built to study the factors affect the seller's credit supply and the platform's supervision intensity. We draw suggestions about how to optimize the credit supply, which include proper intensity of supervision, differentiated supervision strategy, improvements of credit evaluation mechanism and supervision of social organizations. Furthermore, the supervision from authentic social organization works more efficiently to the platform with high profits.

Keywords: online shopping platform, credit supply, credit supervision, game model

1. INTRODUCTION

With the increased usage of the Internet worldwide, the Internet has risen to become one of the most popular way to go shopping. Online shopping, that is, purchases which customers make through various electronic systems has boomed around the world [1]. Forrester Research estimates that US online retail will reach $262 billion and $370 billion by 2013 and 2017, respectively, representing a compound annual growth rate of 10% [2]. Besides the booming US and European markets, the Asian region has also shown a significant growth. In china, online shopping transaction amount in 2014 is roughly equivalent to 10.7% of the total retail sales of social consumer goods [3].

The online shopping platform is an electronic system provided by the third party, which is independent of buyers and sellers. It is a giant electronic shopping mall to promote impulse buying of consumers by the aggressive marketing and promotion strategies adopted by the online stores [4]. The platform offers a series of services to conduct business, which include credit monitoring, information flow, payment and logistics. The online shopping platform can be divided as consumer to consumer and business to consumer in terms of the role of participants. In china, Taobao is the biggest C2C platform and Tmall is a top B2C platform, both are operated by Alibaba. Tmall is expected to compete with other online retailers of higher credit. While, the successful online retailers such as JD, Amazon, Suning and Walmart also act as platform except retailer, which intensify the competition of online shopping platforms.

One aspect of online shopping research is about how consumers perceive online information relevant to their shopping needs, like the importance of perceptual processes on consumers' attitudes and behavioral intentions while shopping online [5][6], the increasing managerial focus on optimizing product presentations on web pages [7] , perceived website complexity[8], website diagnosticity[9], online display factors[10], and visual information quality [11]. Other research compares shopping on online and physical location. Consumers who shop online can be behaviorally different in shopping decisions in comparison to the non-Internet shoppers [12]. Online shoppers will enjoy multiple forms of convenience, these include less physical effort involved, flexibility in terms of when they want to shop, easiness in responding to promotions and advertising, and simple and user-friendly websites [13]. Schultz and Block report details of product preferences and buying scenarios on leading online retailers [14].

However, few research notices the problem of low credit supply of the sellers on online platform. China has the biggest online shopping market in the world and also faces a hurdle of fake and tort. Lack of credit on online shopping platform is becoming more serious, which will shadow the future of e-commerce in china. A credit score is a number that represents an assessment of the credit worthiness of a person, or the likelihood that the person will repay his or her debts, which are generated based on the statistical analysis of a person's credit report [15]. For the sellers on online shopping platform, credit score is mainly accumulated by the evaluation of the buyers who have bought goods from the sellers. The evaluation mechanism cannot work as efficiently as credit bureaus such as Experian, Equifax, and TransUnion in physical world. This study focuses on improvements of the credit supply on online shopping platform, by analyzing the factors affect the seller's strategy of credit supply and the platform's strategy of supervision intensity in the game.

2. MODEL

In the credit supply of online shopping platform, the sellers are the side that supply the credit, the platform is the side that supervises the sellers' supply. The seller's credit supply affects his own performance and the platform's credit and performance. At the same time, the platform's supervision also affects the seller's strategy and performance. In the credit supply problem, the strategies of the seller and the platform interact with each other. Game theory is the method to study how the equilibrium of the strategies reaches, when the players' strategies interact with each other. We give the game model of the credit supply problem.

The players in the game are the seller S and the platform P. The strategy set of the seller is $\theta \in [0,1]$. $\theta = 0$ means the credit supply of the seller is 0. $\theta = 1$ means the credit supply of the seller is 1, which is the complete credit supply. The strategy set of the platform is $f \in [0,1]$. $f = 0$ means the supervision intensity of the platform is 0. $f = 1$ means the supervision intensity of the platform is 1, that is all the incomplete credit supply behavior will be found.

The sales of seller $i(i = 1,2 \cdots n)$ account for $\alpha_i \in (0,1)$ of the platform's sales. The normal profit of the seller is $\gamma \geq 0$, zero credit supply brings the seller extra profits $\omega > 0$. The short-term influential coefficient of the seller's credit to his performance is $\beta_S(\beta_S > 0)$. The long-term influential coefficient of the seller's credit to his performance is $\delta(\delta > 0)$.

The sales of the platform during a period are $M(M > 0)$, which are the sum sales of all the sellers. The profit of unit sales is $R(R > 0)$. The influential factor of the platform's credit to its performance is β_P. The low credit supply of the seller will be mapped into the platform's lower credit, satisfying $\beta_P > \beta_S$. The supervision cost of the platform is $c(c > 0)$. The penalty that the platform gives to the seller's zero credit supply is $k(k > 0)$.

The seller's utility U_S are composed of four parts: the normal profit, the extra profit of low credit supply, the short-term utility loss of low credit supply, and the long-term utility loss of low credit supply. The long-term utility loss is marginally increasing with the level of incomplete credit supply of the seller. Hence, U_S is

$$U_S = \alpha_i M\gamma + (1 - \theta)\omega\alpha_i M - \beta_S(1 - \theta)\alpha_i M\gamma - \frac{1}{2}kf(1 - \theta)^2\delta\alpha_i M\gamma \quad (1)$$

The platform's utility U_P are composed of three parts: the profit brought by the seller's sales, the utility loss from the seller's low credit supply, and the utility loss of supervision cost. The loss of supervision cost is marginally increasing with the intensity of the supervision. Hence, U_P is

$$U_P = MR - \beta_P(1 - f)(1 - \theta)\alpha_i MR - \frac{1}{2}f^2c \quad (2)$$

3. EQUILIBRIUM

The seller chooses the credit supply level θ to maximize his utility. The platform chooses the intensity of supervision f to maximize its utility. According to the first order condition,

$$\partial U_S/\partial\theta = -\omega\,\alpha_i M + \beta_S\alpha_i M\gamma + kf\delta\alpha_i M(1 - \theta)\gamma = 0 \quad (3)$$

$$\partial U_P/\partial f = \beta_P(1 - \theta)\alpha_i MR - fc = 0 \quad (4)$$

We get the reaction function

$$\theta = 1 - \frac{\omega - \beta_S\gamma}{kf\delta\gamma} \quad (5)$$

$$f = \frac{\beta_P(1-\theta)\alpha_i \mathrm{MR}}{c} \quad (6)$$

By putting equation (5) and equation (6) into each other, we get

$$\theta^* = 1 - [\frac{c(\omega - \beta_S\gamma)}{\delta\gamma\beta_P\alpha_i MRk}]^{1/2} \quad (7)$$

$$f^* = [\frac{\beta_P(\omega - \beta_S\gamma\alpha_i \mathrm{MR})}{\delta ck\gamma}]^{1/2} \quad (8)$$

Where, the precondition that (θ^*, f^*) exists is $> max(\beta_S\gamma, \beta_S\gamma\alpha_i \mathrm{MR})$.

3.1 The strategy of seller's credit supply

From equation (7), we get the factors that affect the seller's credit supply θ^*. $\partial\theta^*/\partial\omega < 0$ represents that the higher the extra profit from incomplete credit supply is, the lower credit supply θ^* is. $\partial\theta^*/\partial\beta_S > 0$ represents that the higher the short-term influence of the seller's credit to his performance is, the higher credit supply θ^* is. $\partial\theta^*/\partial\gamma > 0$ represents that the higher the seller's normal profit is, the higher credit supply θ^* is. $\partial\theta^*/\partial\delta > 0$ represents that the higher the long-term influence of the seller's credit to his performance is, the higher credit supply θ^* is. $\partial\theta^*/\partial\beta_P > 0$ represents that the higher the influence of the platform's credit to its performance is, the higher credit supply θ^* is. $\partial\theta^*/\partial\alpha_i > 0$ represents the bigger part the seller's sales is, the higher credit supply θ^* is.

Except the characteristics of the seller, the supervision of platform affects the seller's credit supply too, because the seller's strategy and the platform's strategy are interactive. $\partial\theta^*/\partial c < 0$ represents that the higher the supervision cost of platform is, the lower credit supply θ^* is. $\partial\theta^*/\partial k > 0$ represents that the higher the penalty given by the platform is, the higher credit supply θ^* is. $\partial\theta^*/\partial(MR) > 0$ represents that the higher the sales of platform is, the higher credit supply θ^* is.

3.2 The strategy of platform's supervision

From equation (8), we get the factors that affect the supervision intensity of platform. $\partial f^*/\partial\beta_P > 0$ represents the higher influence of the platform's credit to its performance is, the higher supervision intensity f^* is. $\partial f^*/\partial c < 0$ represents the higher supervision cost of platform is, the lower supervision intensity f^* is. $\partial f^*/\partial k < 0$ represents the higher the penalty given by the platform is, the lower supervision intensity f^* is.

Except the characteristics of the platform, the credit supply of seller affects the platform's supervision strategy too. $\partial f^*/\partial\omega > 0$ represents the higher the extra profit of low credit supply is, the higher supervision intensity f^* is. $\partial f^*/\partial(\alpha_i MR) > 0$ represents the higher profit brought by the seller is, the higher supervision intensity f^* is. $\partial f^*/\partial\alpha_i > 0$ represents the higher rate of sales of sell is, the higher supervision intensity f^* is. $\partial f^*/\partial\beta_S < 0$ represents the higher influence of the seller's credit to its short-term performance is, the lower supervision intensity f^* is. $\partial f^*/\partial\gamma < 0$ represents the higher the normal profit of seller is, the lower supervision intensity f^* is. $\partial f^*/\partial\delta < 0$ represents the higher influence of the seller's credit to its long-term performance is, the lower supervision intensity f^* is.

4. SUGGESTIONS

According to the above analysis, we get the factors that affect the credit supply and the intensity of supervision. By categorizing the factors, four aspects of suggestion are summarized.

4.1 Intensity of supervision

The platform chooses the intensity of supervision by considering three factors: the intensity of supervision f, supervision costs c, and penalty k. The platform makes a choice after balancing the effects of these factors. For sellers, the platform should increase the supervision intensity of the low-credit behavior. But if the supervision intensity increases and the unit supervision cost cannot decrease significantly, the overall supervision costs will increase. If there is a way to decrease the unit supervision cost, the intensity of the supervision can be increased. Increasing the punishment and reward can also improve the efficiency of supervision, while the supervision intensity keeps unchanged. The suggestions for the platform are as follows.

Use big data to supervise credit. Real-time monitoring and analysis of the behavior of both sellers and buyers can automatically find abnormal trading behavior from the massive amounts of data, which will effectively mine the fraud behavior and significantly reduce the supervision costs of platform.

Establish business alliances and achieve mutual supervision. Sellers are grouped into business alliances. Joining into a business alliance is a good credit guarantee and win more credits to the seller. On the other hand, if one seller in the alliance has fraud behavior, every seller in the alliance will be fined. In this way, sellers will monitor mutually, and the platform can reduce investments in supervision.

Grade the penalty. A seller's qualification must be strictly audited before being allowed to open a store on the platform. A risk fund mechanism should be set up. Once the seller has fraud behavior, the risk fund he had paid before won't be returned. The seller's store will be closed under serious fraud cases. Make sure that the lower the level of credit supply is, the higher the penalty is.

Reward the full supply of credit. The rewards include: providing search ranking sorted by the level of credit supply, providing free promotion opportunities to sellers with high credit supply, and setting a credit threshold for the sellers to participate the promotional events held by the platform.

4.2 Differentiated supervision strategy

The factors affect the supervision strategy of platform include the normal unit profit γ, the extra unit profit ω, the long-term influence δ, and the profit contribution to the platform $\alpha_i MR$ of the seller. Sellers with different characteristics act differently in credit supply. Because of the supervision costs, supervision will lack efficiency if adopting same supervision strategy to all the sellers. Therefore, the platform should put more efforts into sellers with the following characteristics.

Sellers with low unit normal profit. These sellers operate the commodity of high homogeneity, industry competition squeezes profit margin. It's difficult to obtain good profit margin, if the sellers have no advantage in the supply channels, the possibility of low credit supply occurs.

Sells with high unit extra profit. These sellers deal with commodities that exist a lot of fake, imitation and brand tort, and extra profits of dishonesty is huge. Then the high possibility of low credit supply occurs.

Sellers who don't emphasize long-term profits. These sellers who haven't been operating on the platform for a long time, pay no attention to the cultivation of loyal customer base, and only chase short-term profits. They usually fake sales and good evaluation to accumulate credit score, attract a large number of customer groups with low price, and conduct a one-time transaction. Then the high possibility of a lower credit supply occurs.

Sellers who contribute a lot profits to the platform. Such sellers are the source of profits and pay a high transaction commissions. Their sales account for a big part of the overall sales and their fraud behavior will bring huge customer loss and profit loss to the platform.

4.3 Improvements of credit evaluation mechanism

β_S reflects the short-term influence of the seller's credit to its operating, which should be the most direct and effective way to restrict the seller's credit supply. But the existing credit evaluation mechanism to calculate the credit score of seller is not a good way to distinguish the seller's credit supply. Sellers on the platform generally have a similar credit score, consumers are difficult to pick out sellers with high credit in terms of credit score. Sellers even use the loophole of credit system to fake sales. The third part logistics companies and staff of the platform can get involved in the fraud under corruption cases. The credit evaluation mechanism cannot fully reflect the sell's credit, and β_S cannot be a constraint on the seller's credit supply. Improvements of credit evaluation mechanism are proposed as follows.

Establish a more reasonable credit evaluation model. Except the buyers' evaluation, more factors should be added into the model such as transaction amount and operating time. The transaction amount can prevent the seller from getting a rapid accumulation of credit by dumping a large number of low-priced goods, then operating goods with high profits. The operating time endows the earlier evaluation with the higher weight, which can prevent faking short-period credit accumulation.

Protect personal information of buyers. Buyers can choose to buy and evaluate the product anonymously after the transaction. It can prevent the seller from calling and threatening the buyer to modify bad comments on the product. This can differentiate the credit score of sellers to a certain extent and make the credit mechanism to play fairly.

4.4 Supervision from social organizations

β_P reflects the influence of the platform's credit to its performance and should be the real evaluation of the platform measured by society. Due to the existence of information asymmetry and lack of information transparency, the true credit of the platform cannot be derived from the buyer's evaluation. So, professional and authentic social organization should get involved to supervise the platform's credit. The proposed supervision from social organization are as follows.

Make the supervision results of social organization fully public. It can enlarge the influence of credit to the platform's performance and put pressure on the platform to increase the intensity of supervision. In this way, the entire e-commerce credit will improve. The fact also proves the effect of social supervision. In January 2015, the State Administration of Industry and Commerce in china made a sample check on the commodities in Taobao. The results showed that there are a lot of fakes and pointed out that Alibaba are irresponsible in several issues: the sellers' qualification and commodity information are not strictly censored, sales management is in a mess, credit evaluation mechanism has drawback, and some internal staffs are involved into the corruption. The US attorney's office noticed the results and initiated the investigation and prosecution. Alibaba's share price had been down in the past months, which pressed Jack Ma to commit to active cooperation with the government departments to combat fakes.

Focus on supervision of the platform with high profit. MR is the platform's profit, the participation of social organization has a big impact on the platform and bring a huge loss to the platform with high profits. So, focusing on the supervision of the platform with high profits is an optimized policy.

ACKNOWLEDGEMENT

This research was supported by Wuhan University of Science and Technology project (2013XG013).

REFERENCES

[1] Lohse, G.L., Spiller, P. (1998). Electronic shopping. Communications of the ACM, 41(7):81–87.

[2] Mulpuru, S. U.S. online, retail forecast, 2012 to 2017. (2013) .Forrester Research. http://www.forrester.com/ US+ Online+ Retail+Forecast+2012+To+2017/fulltext/-/E-RES93281.

[3] Iresearch. Research of online consumer of china in 2015. (2015). http://www.iresearch.com.cn/report/2360.html, 2015-4-23.

[4] Dawson, S., Kim, M. (2009). External and internal trigger cues of impulse buying online. Journal of Interactive Marketing, 3: 20–34.

[5] Jarvenpaa, S. L., Todd, P. A. (1996). Consumer reactions to electronic shopping on the World Wide Web. International Journal of Electronic Commerce, 1(2): 59–88.

[6] Szymanski, D., Hise, R. (2000). E-satisfaction: An initial examination. Journal of Retailing, 76(3): 309–322.

[7] Burke, R. R. (2002). Technology and the customer interface: What consumers want in the physical and virtual store? Journal of the Academy of Marketing Science, 30(4): 411–432.

[8] Nadkarni, S., & Gupta, R. (2007). A task-based model of perceived website complexity. MIS Quarterly, 31(3): 501–524.

[9] Jiang, Z., & Benbasat, I. (2007). The effects of presentation formats and task complexity on online consumers' product understanding. MIS Quarterly, 31(3):475–500.

[10] Jiang, Y., & Punj, G. N. (2010). The effects of attribute concreteness and prominence on selective processing, choice, and search experience. Journal of the Academy of Marketing Science, 38(4): 471–489.

[11] Im, H., Lennon, S. J., & Stoel, L. (2010). The perceptual fluency effect on pleasurable online shopping experience. Journal of Research in Interactive Marketing, 4(4): 280–295.

[12] Soopramanien, G.R., Robertson, A. (2007). Adoption and usage of online shopping: an empirical analysis of the characteristics of "buyers", "browsers" and "non-internet shoppers". Journal of Retailing and Consumer Services, 14 (1): 73–82.

[13] Suki, N.M., Ramayah, T., Suki, N.M. (2008). Internet shopping acceptance: examining the influence of intrinsic versus extrinsic motivations. Direct Marketing International Journal, 2 (2):97–110.

[14] Schultz D. E., Block M.P. (2015). U.S. online shopping: Facts, fiction, hopes and dreams. Journal of Retailing and Consumer Services, 23: 99–106.

[15] Arya, S., Eckel, C. (2013). Anatomy of the credit score. Journal of Economic Behavior & Organization, 95:175– 185.