Live-stream Credit Risk Analysis Based on Dynamic Game Theory

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Abstract: Live-stream e-commerce has been developed dramatically in recent years and COVID lockdown propelled it even further. However, with the increasingly serious problem of lack of integrity, credit risk has become one of the important factors that seriously hinder the healthy development of live-stream e-commerce. In response to this problem, this paper uses the dynamic game theory to systematically analyze the generation mechanism of the credit risk of the two participants in live-stream e-commerce activity, the live merchants and the live platform, and discusses the key factors that affect the occurrence of credit risk. The results show that the degree of violation of live-stream merchants is inversely proportional to the degree of punishment, the discount factor and the probability of credit supervision of the live-stream platform; while the degree of credit supervision of the live-stream platform is inversely proportional to the degree of punishment, the square of the discount factor of live-stream merchant, and the credit supervision of the live-stream platform.

Key words: Live-stream e-commerce, credit risk, game theory, live-stream merchants, live-stream platform

1. Introduction

At the beginning of 2020, the new crown epidemic swept the world and brought unprecedented challenges for the rest of the world. At the same time, the comprehensive line of work, learning and lifestyle is also spawned under the influence of the epidemic, and emerging activities such as housing economy, no contactless economy has changed the consumption and work habits of society. As an emerging consumption method, E-commerce live broadcast is particularly bright. Live e-commerce is quickly accepted and loved by consumers by providing strong interactive and social, immersive shopping experience. In China, as of June 2021, the netizens had exceeded 1.0 billion, more than 70% of the population, more than 10 types of Internet applications in the size of more than 500 million.

Unlike traditional e-commerce, the current e-commerce live broadcast mode is multi-dimensional, more intuitive, more real, and more interactive. Consumers can not only learn about the goods through pictures, but also through short video. The experience of the anchor to the product can make consumers to see all the goods in the goods, which breaking the status of unknown product to consumers in a large extent.

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In the interaction with the anchor during the live broadcast, consumers can tell their questions and needs in real time. The anchor can response in time, greatly reduce the cost of trial error, so that consumers are integrated into the shopping scene. Credit risk modeling is the main research method of analyzing credit risk, and many scholars have analyzed credit risk from the perspective of game theory. Early credit risk modeling is based on the dominant status of static assessment [1-4]. Merton [1-2] has proposed a model for assessing the credit risk of a company by characterizing the company's equity as a call option on its assets.

Study of West [3] demonstrate that the multilayer perceptron may not be the most accurate neural network model, and that both the mixture-of-experts and radial basis function neural network models should be considered for credit scoring applications. Doumpos et. al [4] explores the performance of the M.H.DIS method (Multi-group Hierarchical Discrimination), which is used to develop a credit risk assessment model. With the change of internal demand in credit risk management, the focus of credit risk modeling has been transferred to the dynamic model of the portfolio [6-20].

The study of Hamerle et al. [6] show how the Basel II one factor model can be extended to a model for estimating PDs and correlations. The important advantage is that it uses actual information about the point in time of the credit cycle. Hull et.al [7] have proposed a method for estimating the model's parameters from the implied volatilities of options on the company's equity. The study of Abrahams et.al [8] trace back the root reasons of credit risk focus on the major kinds of market participants, and how each of them is perceived to have contributed to the crisis. Siekelova et al. [9] propose that credit management as the management of trade credit has become very important and they draw up basic theoretical principles for determining the credit limit for individual customers in the company.

In recent years, machine learning methods have been more used to simulate the credit rating process of rating agencies [10-20]. These methods include hidden Markov models [10], neural networks [11-13], support vector machines [14-16], fuzzy systems [17], decision trees [18] and meta-learning approaches [19-20].

Analysis on E-commerce credit risk with game theory has been more and more popular. Dellarocas [21] confirmed in a fully balanced market environment, merchants will still make fraud, because high quality products are higher than low quality products, so merchants often promise to sell high quality products. Zhang et al. [22] discussed the formation of credit risk in E-commerce based on game theory and presents some suggestions for future application of Ecommerce credit. Some scholars [23-25] analyze credit risk in E-commerce based on the evolutionary game model. Wang et al. [23] explore variety learning models in the evolutionary games and give the theory defects of traditional game theory; Nan et al.[24] establish a trust information sharing model and analyze the steady-going state and evolution tendency by replicator dynamics; the results by Li et al. [25] show that increasing the truth rate and the influential power of online Word-of-Mouth can change the unfavorable condition of slack supervision and fake's selling. Credit mechanisms have been established [26, 27]. Yang et al. [26] have established a C2B2C credit supervision mechanism by incorporating the transaction platform as a third party. Kang et al. [27] have proposed a mechanism 'collective Reputation and Trusted Third Party' to achieve the credible trading in online transactions by means of registration fees and cheating punishment.

However, with the emergence and development of live e-commerce, the anchor gradually as the subject of live shopping, and the live e-commerce industry chain continues to improve, and has formed an ecological closed-loop including live merchants, MCN institutions, anchors, and platforms and consumers. This paper mainly analyzes the credit risk of the ecological closed-loop mainly from the perspective of live merchants and platforms. Our contribution is mainly reflected in two aspects. First, we have established a dynamic game model of live broadcast platform and live merchants, secondly, model analysis results show that the credit behavior of merchants and platform is mainly affected by punitive intensity, folding factors, and supervision of the managers.

2. Establishment of the model

It is a dynamic game process between live e-commerce platforms and merchants. E-commerce platform provider will release the various regulatory policies established. Live merchants will make corresponding decisions under the premise of knowing the various regulatory policies. We know that, the larger the supervision of the platform provider, the smaller the breach of contract income, the smaller the degree of default, the greater the punishment. The breach of contract income is greater to the live-income business of short-term interests, that is, the higher the degree of default. At the same time, the larger the supervision and punishment, the smaller the supervision costs. For the live merchants of short-term interests, the live platform should strengthen supervision.

According to the expected utility theory and rational economists hypothesis, the condition for rational economy to actively trustworthiness is that the expected utility when the faction is less than the trustworthiness. Whether the merchant trustworthy in live broadcast depends on its own behavior, while he will trade against default costs in the faction and the possible benefits, live platforms are managed on virtual markets, and weigh against regulatory costs and benefits. Based on whether it is decided to supervise and supervise live merchants. The merchant's defaulting is not only related to the punishment of default, but also related to the supervision of the platform, and the performance of the platform is related to the degree of default and the resulting loss. The behavior results of these two subjects have formed different live shopping credit risks. Therefore, the formation of live shopping credit risk is the result of the game between the merchants and the platform of live broadcast activities.

2.1 Assumption on the game situation

Game situations refer to the opponents, information, and markets facing the participants in the game, and the possibility affect the parameters collection of game results. The real economic environment is complicated. In order to facilitate analysis, the game situation between the e-commerce platform and the e-commerce seller is assumed:

(1) This game is a two-stage dynamic game. The live-stream platform determines the supervision, and then the live-stream merchant determines the degree of violation.

(2) P is the extent of the platform's supervision ($0 \leq P \leq 1$), and Q is the default income of live-stream merchants. We have such a hypothesis that the greater the default probability, the higher the breach of contract income. Meanwhile, the loss caused by this breach of contract is αQ ($\alpha \geq 1$).

(3) If the live-stream merchant's default behavior is discovered, the penalty of the platform is related to the seller's default income Q. Assume that f(Q) represents the platform's penalty for the seller's breach of contract or dishonesty, $\mu(0<\mu\leq 1)$ is the transfer factor, indicating the proportion of the punishment transferred to the net income of the platform, $\Phi(P)$ is supervision costs and $\Phi(P) > 0$, then $\mu f(q)$ is the net income of the platform, supervision costs of the platform are related with the supervision intensity.

(4) The folding factor of the live-stream merchant is δ ($0\leq\delta\leq 1$), it is a function of time preference and time length of the transaction. The value of accounting executors value the current interests, the smaller the δ; the longer the time, the smaller the δ.

(5) Suppose the rest information is common knowledge except for the extent of the live-stream merchant's default and platform supervision.

(6) All default behaviors of the seller can be regulated by the live-stream platform. Since supervision is not implemented in reality because of regulatory costs and other uncertainties, it is possible to be achieved through infinite increase in regulatory costs.

(7) The risk attitude of the live-stream merchant and the platform is risky neutral.

2.2 Basic model

When live business default, the expectations of the merchants and platforms are μ_1 and μ_2, respectively, according to the foregoing hypothesis, we can get:

$$\mu_1 = Q - f(Q)\times P\times\delta \qquad (1)$$

$$\mu_2 = f(Q)\times P\times\mu - P\times\Phi(P) - \alpha\times Q \qquad (2)$$

Set the first derivation of Q equal to zero:

$$\frac{d\mu_1}{dQ} = 1 - P\times\delta\times \dot{f}(Q) = 0 \qquad (3)$$

We have:

$$\dot{f}(Q) = \frac{1}{P\times\delta} \qquad (4)$$

For simple analysis, setting the following relation:

$$f(Q) = \beta\times Q^2 \qquad (5)$$

Here, β is a penalty factor, indicating a penalty of the extent to live merchants, $\mu\times(\beta\times Q^2)$ is the net income of the platform.

We can get the optimal default value of live business.

$$Q^* = \frac{1}{2\times\beta\times P\times\delta} \qquad (6)$$

Get the above formula to μ_2 we have:

$$\begin{aligned}\mu_2 &= \mu\times(\beta\times Q^2)\times P - P\times\Phi(P) - \alpha\times Q \\ &= \frac{\mu}{4\times\beta\times P\times\delta^2} - P\times\Phi(P) - \frac{\alpha}{2\times\beta\times\delta\times P}\end{aligned} \qquad (7)$$

Set the first derivation of P equal to zero:

$$\frac{d\mu_2}{dP} = -\frac{\mu}{4\times\beta\times\delta^2\times P^2} - \Phi(P) - P\times\dot{\Phi}(P) + \frac{\alpha}{2\times\beta\times\delta\times P^2} \quad (8)$$

It has:

$$\frac{2\times\alpha\times\delta-\mu}{4\times\beta\times\delta^2\times P^2} = \Phi(P) + P\times\dot{\Phi}(P) \quad (9)$$

We can get:

$$\Phi(P)=\frac{\mu-2\times\alpha\times\delta}{4\times\beta\times\delta^2\times P^2}+\frac{\gamma}{P} \qquad (\gamma \text{ is a constant}) \quad (10)$$

To simplize the following analysis, let $\gamma = 0$:

It has:

$$\Phi(P)= \frac{\mu-2\times\alpha\times\delta}{4\times\beta\times\delta^2\times P^2} \quad (11)$$

Equation (11) shows that in the case of a given live merchant default, the platform's supervision cost is related with penalty factor *β,* the square of the discount factor and the square of supervision extent. That is, the greater the punishment, the smaller the supervision cost. Therefore, the live platform should strengthen supervision to the live merchants of short-term interests.

3. Model analysis

3.1 Model solution

（1）When $\mu - 2\times\alpha\times\delta< 0$, that is, when $\delta > \frac{\mu}{2\times\alpha}$

It has:

$$\Phi(P) = \frac{\mu-2\times\alpha\times\delta}{4\times\beta\times\delta^2\times P^2} < 0$$

The supervision cost is negative, which does not match the facts.

Since Φ(P) is the increase of the increase in P, and 0≤P≤1

$$\frac{d\mu_2}{dP} = \frac{2\times\alpha\times\delta-\mu}{4\times\beta\times\delta^2\times P^2} - P\times\dot{\Phi}(P) > \frac{2\times\alpha\times\delta-\mu}{4\times\beta\times\delta^2\times P^2} > 0 \quad (12)$$

Therefore, μ_2 about P is incremented.

At this time, the best regulatory intensity P * = 1, the best live merchant default extent is:

$$Q^*=\frac{2\times\alpha\times\delta-\mu}{2\times\beta\times\delta\times P^*}=\frac{1}{2\times\beta\times\delta}$$

Then we can get the optimal solution of the model:

$$(P^*,Q^*) = (1,\ \frac{1}{2\times\beta\times\delta}) \quad (13)$$

This is also a Nash-aerated solution of the model when $\mu - 2\times\alpha\times\delta< 0$.

（2）Model solution when $\mu - 2 \times \alpha \times \delta \geq 0$, that is, when $\delta \leq \frac{\mu}{2\times\alpha}$.

The situation can be discussed in two cases:

① $P^{*2} = \frac{\mu-2\times\alpha\times\delta}{4\times\beta\times\delta^2\times\phi(P)} > 1$, that is, $\Phi(P) < \frac{\mu-2\times\alpha\times\delta}{4\times\beta\times\delta^2}$.

At this time, it cannot be taken to the P value that satisfies the condition. And under this condition, it has

$$\frac{d\mu_2}{dP} = \frac{2\times\alpha\times\delta-\mu}{4\times\beta\times\delta^2\times P^2} - \Phi(P) - P\times\dot{\Phi}(P) = \frac{2\times\alpha\times\delta-\mu}{2\times\beta\times\delta^2\times P^2} - P\times\dot{\Phi}(P)$$

$$< \frac{2\times\alpha\times\delta-\mu}{2\times\beta\times\delta^2\times P^2} - \dot{\Phi}(P) = \frac{2\times\alpha\times\delta-\mu}{2\times\beta\times\delta^2} + \frac{\mu-2\times\alpha\times\delta}{2\times\beta\times\delta^2\times P^3} < \frac{2\times\alpha\times\delta-\mu}{2\times\beta\times\delta^2} + \frac{\mu-2\times\alpha\times\delta}{2\times\beta\times\delta^2} = 0 \qquad (14)$$

Therefore, μ_2 is the reduction function of P.

At this time, the best regulatory intensity P * = 1, the best live merchant default extent is:

$Q^* = \frac{2\times\alpha\times\delta-\mu}{2\times\beta\times\delta\times P^*} = \frac{1}{2\times\beta\times\delta}$

We can get the optimal solution of the model:

$$(P^*, Q^*) = (1, \frac{1}{2\times\beta\times\delta}) \qquad (15)$$

② $0 \leq P^{*2} = \frac{\mu-2\times\alpha\times\delta}{4\times\beta\times\delta^2\times\Phi(P)} \leq 1$, That is, $\Phi(P) \geq \frac{\mu-2\times\alpha\times\delta}{4\times\delta^2\times\beta}$

We can get the following relation from the formula (7)

$$\frac{d\mu_2}{dP} = \frac{2\times\alpha\times\delta-\mu}{2\times\beta\times\delta^2\times P^2} - P\times\dot{\Phi}(P) < \frac{2\times\alpha\times\delta-\mu}{2\times\beta\times\delta^2\times P^2} \leq 0 \qquad (16)$$

Therefore, μ_2 is the reduction function of P.

Due to 0≤P≤1, the best regulatory intensity P * = 0 and the best live merchant default extent is Q *→∞.

We can get the optimal solution of the model:

$$(P^*, Q^*) = (0, k) \quad (k\to\infty) \qquad (17)$$

It can be seen that when $-2\times\alpha\times\delta \geq 0$ and 0≤P≤1, even if the factor $\beta\to\infty$, the optimal supervision is still zero, so the live merchant is drafted, and the default is reduced to make Q*→∞. In other words, in this case, live-stream merchants' fraud cannot be controlled by the optimal incident credit supervision. The fraud can be controlled only the δ value changed to be less than $\frac{\mu}{2\times\alpha}$, which making live-stream merchants with $\delta > \frac{\mu}{2\times\alpha}$ no longer exists. The value of δ depends on the time preferences and time length of the live merchant. In general, the live merchant's time preference is a personal trait, and personal traits are a slow variable, and the live broadcast platform cannot change the type of live business. Therefore, it can only change the length of time. The longer the time interval, the smaller the δ value is; the shorter the time interval, the bigger the δ value will be. Therefore, timely afterward credit supervision is the effective way to reduce such live-stream merchants' default behavior. Of course, the implementation of credit supervision in advance is quite difficult. Because the fraud of live merchants has not happened, even if supervision is carried out, even if supervision is carried out, it is impossible to affect its income. Therefore, improve the timeliness of credit supervision, implement real-time credit supervision, is the only measure to control live merchant fraud.

3.2 The gains of the game and its impact on the player's behavior under different conditions

The above-mentioned game basic model between live-stream merchants and live-stream platforms in different situations, simply analyzes the behavior strategies of both sides in different options. Then, we will analyze the gains of the game and their impact on the active behavior in different situations.

① Live-stream merchants' benefits of different cases

In the above different circumstances, the solution of the model is in the basic model (1), and the live platform and live merchants can be obtained, respectively, the benefits of live merchants when using optimal decisions:

With the solution to the basic model (1) under the above different circumstances, we can get the benefit of live-stream merchants when both sides using optional decisions:

When $\delta > \frac{\mu}{2\times\alpha}$, and the optimal solution is (P*, Q*) = (1, $\frac{1}{2\times\beta\times\delta}$), we have:

$$\mu_1 = Q^* - \beta \times Q^{*2} \times P^* \times \delta = \frac{1}{4\times\beta\times\delta} \quad (18)$$

When $\delta < \frac{\mu}{2\times\alpha}$ and $P^{*2} > 1$, the optimal solution is:

$$(P^*, Q^*) = (1, \frac{1}{2\times\beta\times\delta})$$

It has

$$\mu_1 = Q^* - \beta \times Q^{*2} \times P^* \times \delta = \frac{1}{4\times\beta\times\delta} \quad (19)$$

When $\delta < \frac{\mu}{2\times\alpha}$ and $0 \le P^{*2} \le 1$, the optimal solution is:

$$(P^*, Q^*) = (0, k) \quad (k \to \infty)$$

It has

$$\mu_1 = Q^* - \beta \times Q^{*2} \times P^* \times \delta = k \quad (k \to \infty) \quad (20)$$

According to the formulas (18)-(20), when all live-stream platforms have implemented optimal credit supervision, the expected income obtained by the live merchants is strictly greater than zero. And when the default strategies of live-stream merchants are not implemented, the income is equal to zero. Thus, optimal supervision of the live-stream platform does not eliminate the fraud of live-stream merchants. Therefore, the supervision to eliminate the fraud of live merchants must not be the optimal credit supervision of the live platform.

② Live platform benefits of different cases

When $\delta > \frac{\mu}{2\times\alpha}$, it has:

$$\mu_2=\mu \times \left(\beta \times Q^{*2}\right) \times P^* - P^* \times \Phi(P^*) - \alpha \times Q^*$$

$$=\frac{\mu}{4\times\beta\times\delta^2} - \frac{\mu-2\times\alpha\times\delta}{4\times\beta\times\delta^2} - \frac{\alpha}{2\times\beta\times\delta}=0 \quad (21)$$

When $\delta < \frac{\mu}{2\times\alpha}$ and $P^{*2} > 1$, it has:

$$\mu_2=\mu \times \left(\beta \times Q^{*2}\right) \times P^* - P^* \times \Phi(P^*) - \alpha \times Q^*=0 \quad (22)$$

When $\delta < \frac{\mu}{2\times\alpha}$ and $0 \le P^{*2} \le 1$, it has

$$\mu_2=\mu \times \left(\beta \times Q^{*2}\right) \times P^* - P^* \times \Phi(P^*) - \alpha \times Q^* = -\alpha \times Q^* = -\alpha \times k \; (k \to \infty) \quad (23)$$

According to (21-23), in all possible cases, even if the live broadcast platform implements the optimal credit supervision, the platform's expected revenue is still less than or equal to 0; even in the process of implementing credit supervision in the platform The social welfare loss, $\alpha = 1$ and $\mu = 1$, the expected revenue of the platform is still less than or equal to 0.

According to the formulas (12) and (16), the optimal credit supervision P^* depends on the penalty coefficient β and the refractory factor δ. And β can affect the optimal credit supervision P^* only in the case of $\delta \le \frac{\mu}{2\times\alpha}$ conditions, in the case of $\delta > \frac{\mu}{2\times\alpha}$, regardless of how the β changes, it does not affect the optimal credit supervision P^*. Therefore, as the basic conditions for efficient credit supervision, β and P exist as preferred: first distinguish different types of live merchants, secondly default penalty of live merchant to be perceived, and then the optimal regulatory intensity.

Why do different types of live broadcast merchants are the primary condition for implementing effective credit supervision? Moreover, after distinguishing between different types of live broadcast merchants, it is also necessary to distinguish default penalty of live merchant to be perceived. We can interpret from the perspective of credit regulation mechanism. In fact, like traditional entity markets, when live merchants in the virtual market participate in virtual social activities (such as transactions) and corresponding behavior, online traders with same participation index(including cultural factors such as values, transaction motivation, perceived and actual differences and participation) are naturally gathered into a group of groups.

They participate in the formation of virtual social order with their common participation index, in which they conflict and coordinate with groups with different participating indices. The credit regulation (hidden or dominant) is one of the most important organizational parts of social order, and they are not only the result of interest conflicts and coordination between the different participants of the virtual market according to different participating indices, but also the result of long and repeated game of participants. Moreover, the performance of different online traders' credit rules is also different due to their feelings and attitude. That is, the behavior of live merchant is not only different from the performance of the credit order, but also the compliance of the credit order. Different types of online traders naturally become the primary premise for implementing effective credit supervision. The punishment is only known to be perceived by the online traders to have an impact on their feelings and attitudes, which affects their behaviors and choices on credit contracts.

4. Conclusions

The results show that the degree of violation of live-stream merchants is inversely proportional to the degree of punishment, the discount factor and the probability of credit supervision of the live-stream platform; while the degree of credit supervision of the live-stream platform is inversely proportional to the degree of punishment, the square of the discount factor of live-stream merchant, and the credit supervision of the live-stream platform. The appropriate goal of the credit supervision of live platforms is not to eliminate the fraudulent behavior of live merchants, but to control the fraud behavior of live merchants, the only measure of such fraudulent behavior is to improve the timeliness of credit supervision; effective credit supervision requires additional cost. The basic conditions for the implementation of effective credit supervision are in order of priority: first distinguish between different types of live merchants, secondly default penalty of live merchant to be perceived, and then the optimal regulatory intensity. This has important revelation on the actual virtual market credit management.

References:

[1] Merton, R., On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance, 1974, 29: 449-70.

[2] Merton, R., On the Pricing of Contingent Claims and the Modigliani-Miller Theorem. Journal of Financial Economics, 1977, 5: 241-249.

[3] West, D., Neural network credit scoring models. Computers & Operations Research, 2000, 27: 1131-1152.

[4] Doumpos, M., Kosmidou, K., Baourakis, G., Zopounidis, C., Credit risk assessment using a multi-criteria hierarchical discrimination approach: A comparative analysis, European Journal of Operational Research, 2002, 138:392-412.

[5] Altman, E.I., Saunders, A., Credit risk measurement: Developments over the last 20 years. Journal of Banking and Finance, 1998, 21: 1721-1742.

[6] Alfred, H., Thilo, L.，Daniel, R., Credit Risk Factor Modeling and the Basel II IRB Approach, Discussion Paper Series 2: Banking and Financial Supervision No 02/2003.

[7] John, C.H., Izzy N., Alan, D., White, Merton’s model, credit risk and volatility skews, Journal of Credit Risk, 2004, 1.

[8] Abrahams, C., Zhang. M.Y., Credit Risk Assessment: The New Lending System for Borrowers, Lenders, and Investors., 2009, SAS Institute Inc., Cary, North Carolina, USA.

[9] Anna, S., Boris, K., Ivana, W., Impact of credit risk management, Procedia Economics and Finance, 2015, 26: 325-331.

[10] Petropoulos, A., Chatzis, S.P., Xanthopoulos, S., A novel corporate credit rating system based on Student’s-t hidden Markov models. Expert Systems with Applications, 2016, 53:87-105.

[11] Zhong, H., Miao, C., Shen, Z., Feng, Y., Comparing the learning effectiveness of BP, ELM, I-ELM, and SVM for corporate credit ratings. Neurocomputing, 2014, 128:285-295.

[12] Hajek, P., Municipal credit rating modeling by neural networks. Decision Support Systems, 2011, 51(1):108-118.

[13] Hajek, P., Vladimír, O., Credit rating modelling by kernel-based approaches with supervised and semi-supervised learning. Neural Computing and Applications, 2011, 20: 761–773.

[14] Huang, Z., Chen, H., Hsu, C.J., Chen, W.H., Wu, S., Credit rating analysis with support vector machines and neural networks: a market comparative study. Decision support systems, 2004, 37(4): 543-558.
[15] Kim, K.J., Ahn, H., A corporate credit rating model using multi-class support vector machines with an ordinal pairwise partitioning approach. Computers & Operations Research, 2012, 39(8): 1800-1811.
[16] Chen, C.C., Li, S.T., Credit rating with a monotonicity-constrained support vector machine model. Expert Systems with Applications, 2014, 41: 7235-7247.
[17] Hajek, P., Credit rating analysis using adaptive fuzzy rule-based systems: an industry specific approach. Central European Journal of Operations Research, 2012, 20: 421-434.
[18] Hajek, P., Michalak, K., Feature selection in corporate credit rating prediction. Knowledge-Based Systems, 2013, 51:72-84.
[19] Pai, P.F., Tan, Y.S., Hsu, M.F., Credit rating analysis by the decision-tree support vector machine with ensemble strategies. International Journal of Fuzzy Systems 2015, 17: 521-530.
[20] Hajek, P., Olej, V., Predicting firms' credit ratings using ensembles of artificial immune systems and machine learning - An over-sampling approach. Papadopoulos HIFIP International Conference on Artificial Intelligence Applications and Innovations, Springer, Berlin Heidelberg, 2014.
[21] Dellarocas, C., Efficiency and Robustness of Binary Feedback Mechanisms in Trading Environments with Moral Hazard. Cambridge, MA, 2003.
[22] Zhang N.N., Wei, X.J., Zhang, Z.Q., Game theory analysis on credit risk assessment in E-commerce, Information Processing and Management, 2022, 59:102763.
[23] Wang X.J., Quan, J., Liu, W.B., Study on evolutionary games and cooperation mechanism within the framework of bounded rationality, System Engineering-Theory & Practice, 2011, 31: 82-93
[24] Nan, X.K., Yao, G.X., evolutionary game analysis on sharing of trust information in B-C Electronic Commerce, Technology Economy and Management Research, 2013, 8:14-18.
[25] Li, J., Zhang, R., Xu, Y., Evolutionary game between E-commerce platform supervision and merchants selling fakes, Journal of Systems Engineering, 2018, 33: 649-661.
[26] Yang, F.M., Wang, A.Y., Wu, J., Designing credit supervision mechanism in C2B2C e-commerce based on game theory, System Engineering-Theory & Practice, 2017, 37(8): 2102-2110
[27] Kang, W.L., Wang, L., Jiang, Y.N., Online Trust transactions through an Incentive Mechanism based on Trusted Third Party, Journal of System & Management. 2016, 25: 821-828.