Information supervisory model for financial risk prevention and control based on twin-SVM

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Abstract: Aiming at the problems of poor effect and low accuracy of traditional financial market risk prevention and control methods, a financial risk prevention and control information monitoring model based on double support vector machine is proposed. The improved support vector machine and asymmetric COvAR data were combined with covariance operation to reduce the actual tail risk overflow. Through financial aggregation and covariance tail data of current characteristic financial system, the spillover effect of financial risk is obtained. According to the extreme value statistical analysis theorem, it is determined that the current financial risk gradually obeys the extreme value. In order to verify the effectiveness of the method, the financial data from 2012 to 2018 provided by a bank were used as experimental samples to conduct simulation experiments. Experimental data show that the proposed method has lower boundary cost and higher market arbitrage, and has a strong market applicability.

Keywords: financial risk; dataset; support vector machine; SVM.

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1 Introduction

Finance is an important part of national and social economic development and economic system construction, and also one of the core pillars. Once there is financial risk trail, it will not only seriously hinder the rapid and stable operation of the current national economy, but also be more likely to affect the international financial market overseas through the risk transmission mechanism, leading to greater financial problems (Yong, 2018). Therefore, it is of great significance to construct an information supervisory model for financial risk prevention and control with strong adaptability and reasonable structure so as to effectively control the current economic system and avoid economic crisis by using risk prevention and control information. Therefore, how to construct an information supervisory model for financial risk prevention and control with certain advantages is one of the core issues studied by modern financial management departments.

Liu et al. (2018) proposes a financial risk prevention and control method based on particle swarm optimisation. This method uses binary particle swarm optimisation to select feature subset, and optimises the parameters of support vector machine by combining with the indicator system for financial risk characteristics of supply chain. This method can improve the accuracy of risk prevention and control, but its application scope is limited. Cai (2018) uses FCM clustering and wavelet clustering algorithms in data mining technology, and introduces reconstruction prediction model of phase space in chaos theory. RBF neural network model is used as fitting function to get the prediction map of financial risk. This method can improve the accuracy of prediction, but the stability of the system is poor. Gao et al. (2018) uses probability calculation tree method to verify the uncertainty of user behaviour by calculating the probability of financial risk prevention and control. The discrete-time Markov chain model can truly describe the probability distribution of investors' purchase and redemption, and determine the probability of users' purchase or redemption behaviour. However, this method has data defects and has poor risk prediction effect on financial markets.

Because the current methods do not use financial aggregation and covariance data to prevent and control financial risks, it results in poor effectiveness and low accuracy of prevention and control methods. In order to solve the problems existing in the current methods and achieve effective prevention and control of financial risks, an extremum evaluation method based on binary POT is introduced to determine the results of supervision and calculation, and a financial risk prevention and control information based on twin-SVM is proposed. The improved traditional support vector machine and asymmetric COvAR data were combined with covariance operation to reduce the actual tail risk. Through covariance tail data, the spillover effect of financial risks can be obtained. The extreme statistical item analysis theorem is used to realise that the current financial risk is asymptotically subject to the extreme value, and the binary POT extreme value is used to evaluate the regulatory calculation result. And set up simulation experiment to verify the effectiveness of the method on financial risk prevention and control information supervision.

2 Design of supervisory model for financial risk prevention and control information based on twin-SVM

2.1 Prevention and control information supervision process design

In order to effectively reduce the boundary cost, reduce the influence of market arbitrage and strengthen the prevention and control of financial risks in the market, a twin-SVM based financial risk prevention and control information supervision model was designed. It is assumed that for the current financial market *i*, there are two kinds of situations at any time of financial operation: normal situation and risk-focused situation, which are expressed by risk state indicator variables $y^{(i)} \in \{-1, +1\}$ respectively. Among them, –1 indicates that the current financial market *i* is in normal financial operation and has not issued a certificate of financial crisis, +1 indicates that the financial market *i* is concerned about risks, indicating the possibility of financial crisis. In addition, each financial moment contains the corresponding variables of n-dimensional financial characteristic indicators as follows: $x_d^{(i)} = (x_1^{(i)}, x_2^{(i)}, \ldots, x_n^{(i)})$, each corresponding component in the formula represents the risk characteristic indicators of the current financial market i, that is, the inducer of the current financial risk information (Izadi and Safdarian, 2018). At this time, its internal characteristic indicator constitutes the data sample point $(x_d^{(i)}, y^{(i)})$.

Because this discussion is about the prevention and control of financial risk information, that is, the financial risk information of the eigenvector machine is used to determine future risk factors, and the current data sample set can be constructed with the current $t - 1$ data feature samples at different moments (Crisóstomo and Couso, 2018). What is worth the subject is that since such a sample set is also an asymmetric sample set, data conversion is required. Because SVM has a small number of support vectors, which determines the final result and is not sensitive to outliers, it can catch key samples. Moreover, this algorithm is simple and has good ‘robustness’. Therefore, twin-SVM is used to train the optimal classification function on the current sample set. To solve the optimisation problem by using $y(i) = f(x)$ to represent the information supervision risk model currently designed. The framework formulas are listed as follows:

$$\begin{aligned} &\min \frac{1}{2}\left\| w_{\pm 1} \exp\left(-\gamma \left| x^{(i)} - x_j \right)^2 \right\| \\ &\text{s.t.} \quad \pm\left(w_{\pm 1} \exp\left(-\gamma \left| x^{(i)} - x_j \right)^2 \right) \\ &\qquad \xi \pm \geq 0 \end{aligned} \tag{1}$$

It should be noted that in the above formula, +1 and –1 can be regarded as sample data of financial data variables and constants. w is the current constraint threshold; j is the relaxation variable, and the following formula has the same meaning (Partey et al., 2018). The above-mentioned core framework formulas are only original formulas and can not be directly applied to prediction. In order to find the optimal problem, Lagrange function should be introduced.

$$L\left(w_{\pm 1}, b_{\pm 1}, \zeta_{\pm 1}, \alpha_{\pm 1}\right) = \frac{1}{2} w_{\pm 1} \exp\left(-\gamma \left| x_{j,d}^{(i)} \right)^2 + \exp\left(-\gamma \left| x_{j,d}^{(i)} - e_{\pm 1} \right)^2 - \zeta_{\pm 1}, \tag{2}$$

In the formula, $\alpha_{\pm 1}$ represents the current Lagrangian data multiplier. The optimal classification function can be obtained by deriving formula (2) and finding the extremum, to construct the feature as a classification combination.

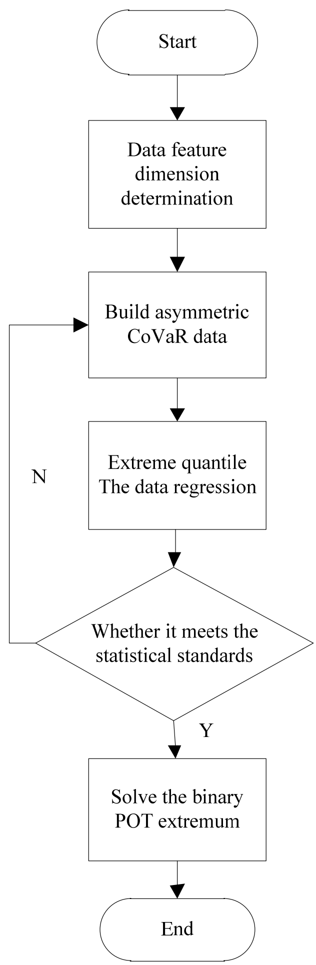
$$\begin{cases} E_1 = J_{pbr} J_m J_p E_{\exp} J_{pbr} \left(E_r + E_m\right) \\ E_2 = J_{pbr} J_m J_p E_{\exp} J_{pbr} \left(E_r + E_m\right) \\ E_3 = J_{pbr} J_{\exp} J_p E_{\exp} J_{pbr} J_{pbr} \left(E_r + E_m\right) \\ E_4 = J_{pbr} J_m J_{\exp} E_{\exp} J_{pbr} J_{pbr} J_{pbr} \left(E_r + E_m\right) \end{cases} \tag{3}$$

Formula (3) shows the data classification combination with existing features, because *pbr* represents dual features, m and p are the ordinal numbers of different dimensions. Dimension comparison formulas can be obtained by optimising the current dimension.

$$\begin{cases} E_1 = \frac{\sqrt{2}}{4} E_0 \begin{bmatrix} -\exp(-i\phi) + \exp(-i\phi) \\ 0 \end{bmatrix} \\ E_2 = \frac{\sqrt{2}}{4} E_0 \begin{bmatrix} 0 \\ \exp(-i\phi) + \mathrm{expp}(-i\phi) \end{bmatrix} \\ E_3 = \frac{\sqrt{2}}{4} E_0 \begin{bmatrix} 0 \\ \exp(-i\phi) - \exp(-i\phi) \end{bmatrix} \\ E_4 = \frac{\sqrt{2}}{4} E_0 \begin{bmatrix} \exp(-i\phi) + \exp(-i\phi) \\ 0 \end{bmatrix} \end{cases} \tag{4}$$

$i\phi$ is defined as the state indicator variable in the formula, and the above is the core idea of calculation (Furlong et al., 2017).

Figure 1 Supervision analysis process



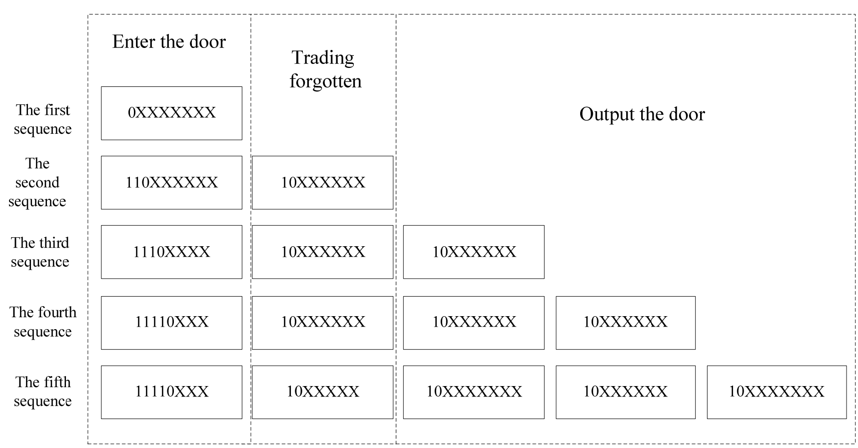
In addition, because SVM cannot apply asymmetric model, asymmetric COvAR data is selected in data processing. This data has a certain confidence level within a certain period of time, and then according to covariance operation, it can effectively reduce the actual tail risk spillover (Partey et al., 2018; Pavão et al., 2017). In addition, in the regulatory model, the synchronous application of calculation is divided into regression thinking, and statistical judgment is made by inferring the quantile of financial extreme conditions and reviewing the model (Pavão et al., 2018; Meyer et al., 2017). Binary POT extremum analysis is used to determine the basis of judgement. Its monitoring process of prevention and control information is as shown in Figure 1.

The following are the core parts of the development steps.

2.2 Acquisition of asymmetric CoVaR data

In order to reduce the actual tail risk overflow, the procedure of acquiring asymmetric CoVaR data was designed. VaR can be seen as a huge loss to a certain financial supply or a clear financial market portfolio and financial institutions according the current financial market theoretical factors, exchange rate risk factors and other related market volatility within a certain period of time and confidence level (Zopounidis et al., 2018). VaR can be seen as a risk measurement of the current market economy system, its purpose is to combine the investment impact brought by the current market factors with the current market sensitivity change law. CoVaR, on the other hand, represents the spillover effect of current financial risks mainly through covariance tail data of financial aggregates and current characteristic financial systems. Because this effect comes directly from the transaction risk of current financial markets and indirectly affects data prices, it has a certain guiding effect on current financial markets. It can be seen as the direct sign of liquidity spiral under the current market economy system. Generally, it can be divided into three indicators: input gate, transaction forgetting and output gate. Input gate refers to the current transaction risk input, transaction forgetting and output gate, which belongs to derivative data indicators, and its significance has the characteristics of reference. Detailed reference is shown in Figure 2 (Stehlík et al., 2017).

Figure 2 Diagram of logic gate of CoVaR data



During the financial crisis, its homogeneous institutional nature will lead to losses in similar financial markets. So CoVaR data is designed and applied as the basic data.

CoVaR is a state variable function of the current financial risk market, which can be described as the dependence impact data of tail risk in the current financial institutions (Sharma et al., 2017; Izadi and Safdarian, 2017). Assuming that the best institutional return of the explanatory variable is X_t the market explanatory variable is M_t, and the relationship between them is linear. The following two variable equations are designed and established:

$$M_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \tag{5}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i} \tag{6}$$

In the above formulas, M_{t-1} represents the highest single sequence lag of the current data variables, and X_t^i is the average stock return on the current financial market (Bonnafous et al., 2017).

The actual and conditional risk values of current financial institutions can be obtained by applying the above formulas.

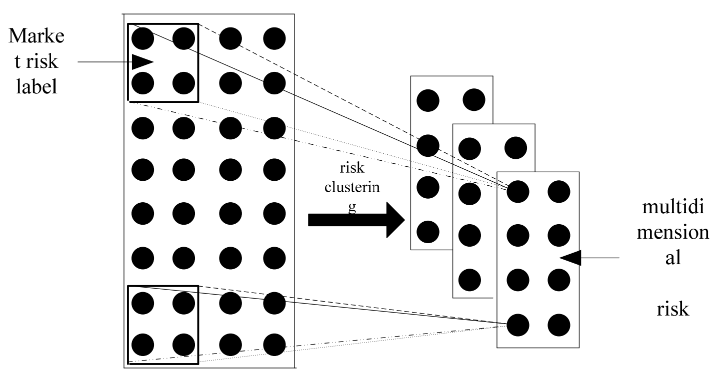
$$VaR_t^i(\tau) = \alpha_t^i + \gamma_t^i M_{t-1} \tag{7}$$

$$CoVaR_t^i(\tau) = a^{system|i} + \beta^{system|i} VaR_t^i(\tau) + \gamma^{system|i} \tag{8}$$

At the same time, because financial institutions contribute to the current risk:

$$\Delta CoVaR_t^{system|i} = \begin{cases} CoVaR_t^i(\tau) - CoVaR_t^i 50\% \\ \beta^{system|i}\left(VaR_t^i(\lambda) - VaR_t^i 50\%\right) \end{cases} \tag{8}$$

Figure 3 Microscopic sketch of risk spillover conversion



If the value of *VaR* is negative, it represents a certain loss in the current financial market. When considering the loss data, we can describe the corresponding area of the current decline in institutional returns. At this time, the monitoring data reflect the impact of institutional system security contribution under the current objective condition of 1% pressure indicator and credit constraints of market economy. In the *CoVaR* data, the value of $\beta^{system|i}$ can reflect the average risk contribution level of the whole data template to the current financial market access rules under the current institutions, but it does not need to consider the actual comparison of the current financial institutions (Lin et al., 2018). Because the estimated $\beta^{system|i}$ value will underestimate the liabilities of banks' data assets, it has obvious impact on the current financial market. Therefore, the application of systemic spillover data of financial tail risk can clearly measure the systemic risk spillover of the current financial market structure. The micro-schematic diagram of the effect transformation is as shown in Figure 3.

In CoVaR financial data, nonlinear financial expectations of market may lead to fluctuations in asset returns of current financial institutions. This part of volatility data may lead to a further increase in the loss-of-return coefficient and appears symmetrical sensitivity data of the tail linkage of new financial models. Therefore, in the actual application process, once the same asset price spiral in the market appears in the CoVaR data, the following propositions can be designed:

Proposition 1: qt this time, the return rate defined by CoVaR data refers to the actual distribution of multiple quantiles q, and its calculation formula is as follows:

$$\Pr\left(X^i \leq VaR_t^i\right) = q \tag{10}$$

At this time, X^i represents the highest financial loss in the current market, and VaR_t^i represents the average evaluation loss of the current financial institutions in the financial market. At this point, VaR_t^i is negative, and the loss of drastic data turbulence may exceed 1%.

Proposition 2: $\Delta CoVaR_q^j$ denotes the current risk event conditions of financial institutions, at which point the definition of risk probability distribution can be provided by q-quantile conditions:

$$\Pr\left(X^i \leq VaR_t^i \middle| C\left(x^i\right)\right) = q \tag{11}$$

According to the above two propositions, we can further enrich the application scope of current CoVaR data and provide a measurement difference for subsequent supervision.

2.3 Extreme quantile regression

The risk sample is one of the key factors of financial risk prevention and control information. Therefore, the design needs to apply the CoVaR financial data sample established above to realise the calculation of CoVaR financial data under the framework of extreme quantile regression. The quantile regression calculation method is given below. First of all, the form of expression is constructed.

Let $F_y(y)$ and $Q_y(\tau)$ be the positive sequential distribution function of the current financial random variable Y and the positive τ quantile function. $F_Y(y|x)$ and $Q_Y(\tau|X)$ are the financial mathematical conditional distribution functions of Y and the current data extreme fraction of τ under the actual given financial variable data $X = x$, respectively. Relative variable X and financial random variable Y have similar covariance points. At this time, in the financial data quantile regression, $F_Y(y)$, $F_Y(y|x)$, $Q_y(\tau)$ and $Q_Y(\tau|X)$ can be constructed as follows:

$$
\begin{aligned}
&F_y(y) = \Pr[Y \leq y] \\
&F_Y(y|x) = \Pr[Y \leq y \mid X = x] \\
&Q_y(\tau) = \inf\left\{y : F_y(y) > \tau\right\} \\
&Q_Y(\tau \mid X) = \inf\left\{y : F_Y(y|x) > \tau\right\}
\end{aligned} \tag{12}
$$

In the above formula, condition τ denotes that $Q_Y(\tau|X)$ of the current quantile regression function is a function of x, and that the current independent variables of financial data have an impact on data risk in different quantiles (Ameur et al., 2018). When the quantile τ is larger than the quantile under the current extreme risk, $Q_Y(\tau|X)$ can be called the extreme quantile regression function under the current risk data. The following are the framework of regression function and the definition of linear distribution:

$$Q_Y(\tau \mid X) = x_T \beta(\tau) \tag{13}$$

By solving the problem, we can get:

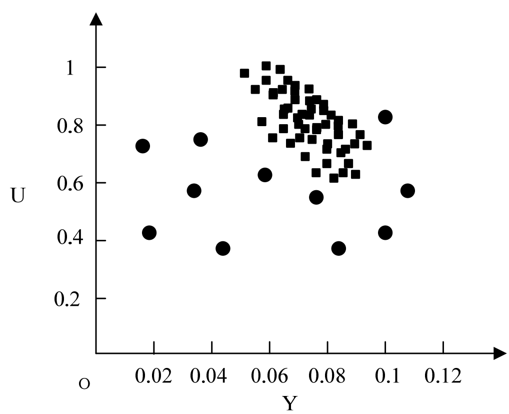
$$\min_{\beta \in R0} \sum_{i=1}^{n} \rho_\tau \left(y_i - x_i^T \beta\right) \tag{14}$$

According to the above formula, the actual risk assessment of current $\beta(\tau)$ can be obtained, where $\rho_\tau(u) = (\tau - 1(u \leq 0))u$, then according to formula (14), it can obtain:

$$\min_{\beta \in R0} \left[\sum_{y \geq xT\beta} \tau \left| y_i - x_i^T \beta \right| + \sum_{y \geq xT\beta} 1 - \tau \left| y_i - x_i^T \beta \right| \right] \tag{15}$$

Where, the value of τ ranges from 0 to 1, and different risk assessment values can be obtained according to the current coefficient vector.

Figure 4 Diagram of risk relationship between *Y* and *U*



The above quantile data regression calculation of financial extreme risk needs to establish the following data assumptions for calculation. It is assumed that the risk condition location and tail risk of the current risk dependent variable follow the iteration and distribution law of Pastore data. In practice, the tail data of its distribution function needs to be attenuated to the current risk function, the power function or the forward regular function. Generally, the generalised Pastore function data includes the risk thickness at the tail of the absolute value of the current risk data in time.

Let the current random variable Y and the random variable U have an iterative risk relationship as shown in Figure 4.

According to the risk relationship between Y and U shown in Figure 4, the quantification function Qu of U is determined. The data value of the downward minimum point of the data function represented by Qu is $Q_u(0)$. At present, the downward minimum of random variable Y can be replaced by negative infinity. When data iteration occurs, the value of risk relationship between Y and U is the same. In this case, the downward minimum point data of Y is $Q_Y(0) \geq -\infty$under random variables and the range of U is $Y - Q_Y(0)$, then under risk condition, $Q_u(0) = -\infty$ and $Q_u(0) = 0$. In this case, the tail risk data if distribution functions Qu and Fu under the linear data are determined by the Pastore distribution hypothesis:

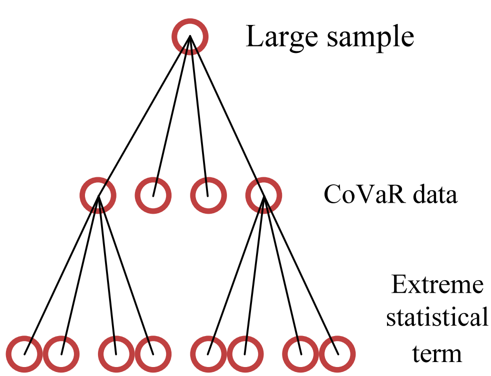
$$Qu(\tau) : L(\tau) \cdot \tau^{-\zeta}, \tau \tag{16}$$

$$F_U(u) : L(u) \cdot u - \zeta \tag{17}$$

In the above hypothesis formula, the value of ζ is not equal to 0, and $L(u)$ and $L(\tau)$ represent the actual quantile function values of τ and U respectively. After determining the expression of extreme quantile, the regression statistical inference under the condition of risk calculation is formally carried out. The order statistics of risk environment are determined based on the current CoVaR data. In the current calculation of extreme quantile regression evaluation, the decisive coefficient of the quantile regression equation is set, and $\beta(\tau)$ is the ordinal statistical quantity of the current quantile regression, in which τT represents the direct statistical order of the current τ quantile. $\{\tau_T, T\}$ is constructed as the ranking order of the current computing centre. When the value of T is positive and infinite, we can affirm that $\{\tau_T, T\}$ has extreme statistical item.

Under the condition of large sample of current financial market risk, according to the above analysis theorem of extreme statistical term, depending on the sequence evaluation of risk centre, it can determine that the gradual obedience of current financial risk to extreme value, so fundamentally, data extreme statistics can be regarded as data splitting process, as shown in Figure 5.

Figure 5 Data splitting legend (see online version for colours)



According to the risk condition of large scale sample, the order of extreme risk can be determined according to the current extreme value theorem. Further CN-QR risk statistical samples are established.

The sample of CN-QR risk statistics is to divide the sample extreme quantile under the current financial risk data and determine the maximum limit distribution of $Q_y(\tau)$. For any current integer, T value is positive and infinite. A formula for calculating fractional statistics is established.

$$Z_T(k) = A_T\left(Q_y(\tau) - Q_Y(0)\right) \rightarrow Z(k) = \frac{\sqrt{k}(T)}{K - T} \tag{18}$$

When K is greater than 1 and KT is positive, it can be concluded that:

$$A_T = \frac{\sqrt{\tau_T T}}{Q_y} \tag{19}$$

A_T is a risk scale factor in the above formulas, which can be obtained by data risk function and its quantile is easily accessible. According to the regressive data evaluation equation of the extreme quantities mentioned above, the relationship evaluation of the statistical sub-quantities of the current CoVaR data can determine the parametric relationship in the above equation, and then calculate the extreme tail pressure of the regular data in the current financial market, so as to determine the risk value and condition of the current financial market.

2.4 Implementation of financial risk prevention, control and supervision

The above analysis process reveals the preparation process of asymmetric CoVaR data relationship and the regression relationship of extreme quantile, and determines the risk conditions of the current data. Finally, according to the evaluation of the extreme value of binary POT, the final regulatory estimation results can be determined. Multivariate extremum can be used to describe the same dependency structure of connection function and determine the separation edge dependency of risk coefficient to construct Frechet. The distribution form is:

$$F(x) = \begin{cases} \exp\left[-(1+\varepsilon x), x > -\frac{1}{\varepsilon}\right] \\ 0, \quad x \le -\frac{1}{\varepsilon} \end{cases} \tag{20}$$

In the above formulas, $\varepsilon > 0$, $x = \frac{(x_n - \beta_n)}{\alpha_n}$, and there are some rules when n tends to be positive infinite and non-degenerate risk distribution. Where α_n represents the actual risk distribution sequence under the current risk scale factor, β_n represents the current actual position sequence, ε represents the current position shape parameters.

In this case, $F(x, y) = \Pr(X < x, Y < y)$, which is used to represent the binary risk quantity distribution of current risk prevention and control information. In the known binary risk extreme value distribution, $F_X(x)$ and $F_Y(y)$ are used to represent the random variables of current risk edge, respectively. *S* and *T* need to obey the current distribution random variables.

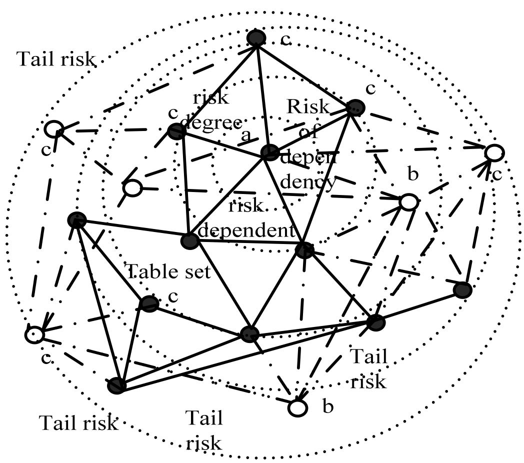
$$S = \frac{-1}{\log F_x(x)} \\ T = \frac{-1}{\log F_y(y)} \tag{21}$$

According to the current risk data, the structural probabilities of proposition (X, y) and proposition (*S*, *T*) are determined as follows:

$$p(q) = P[F(T) > q | F(s) > q] \tag{22}$$

Whereas *P* represents the pickands dependent data function of data risk, there is a joint survival comparative relationship of current market prevention and control information as shown in Figure 6.

Figure 6 Comparison of joint survival of market prevention and control information



According to the current relationship to determine the risk tail relationship, combined with the above COvAR data, we can complete the current financial risk information assessment.

$$\chi = \lim_{s \to \infty} \frac{2 \log P(S > s)}{\log P(T > s, S > s)} \tag{23}$$

- when χ is 1, then (*S*, *T*) risk data are in a state of mutual dependence, and *S* and *T* are in a state of complete independence.
- when χ equals zero, (*S*, *T*) is in the independent state of risk correspondence.
- when χ is greater than 0, (*S*, *T*) is in the corresponding state of mutual risk.
- when χ is greater than 1, (*S*, *T*) is in a sub-asymptotic state.

According to the corresponding state mentioned above, the data extremum and progressive data relationship between random variables of current risk data can be determined. Risk is in four levels from strong to weak. Through class division, it can directly reflect the current risk environment of market information and realise prevention, control and supervision.

3 Analysis of experimental data

In the virtual environment, the design of the experiment relies on the financial samples provided by a bank from 2012 to 2018. The proposed method and the method in Liu et al. (2018) were used to conduct risk assessment and prediction on samples, and the boundary cost risk prediction and market arbitrage mechanism measurement were taken as verification objectives. Through the information of the interest rates for interbank offerings, negative interest rates and Shanghai stock composite indicator, the experimental financial results are prepared, to depict the current market-oriented relationship between supply and demand of financial risk supervision funds, and to some extent reflect the current liquidity and capital variables in market. The return of Shanghai Stock Exchange represents the capital price of the current stock market, while the interbank interest rate reflects the degree of financial lending in the market, and the negative interest rate determines the liquidity change in the current market. After data analysis and collation, the experiment will describe the above three data samples to develop corresponding statistical data, and the chart is as shown in Figure 7.

According to the above financial environment, the experiment takes the current design of information supervisory model for financial risk prevention and control as the core verification object, and the traditional risk supervisory model based on support vector machine is used as comparative model to carry out risk prevention and control comparison. Table 1 shows the sample statistics of the current experimental environment:

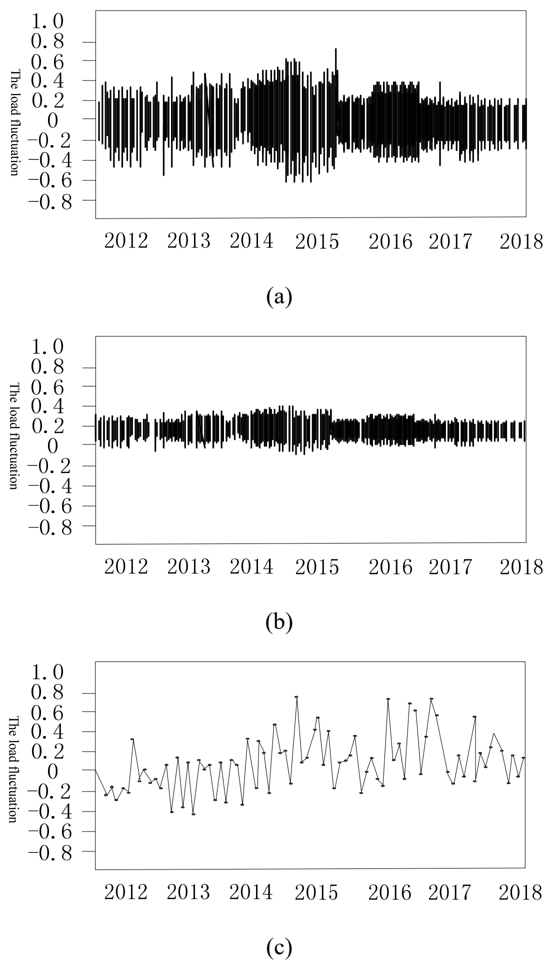
Table 1 Sample statistics

	The mean	*The maximum*	*The minimum value*	*The standard deviation*	*JB statistics*
Put down the	–0.25853	0.85956	–0.75218	0.07899	0.28565
Negative interest rates	0.04896	5.95585	–4.25896	0.05872	0.36852
The Shanghai	3.28584	11.058	1.3596	1.36955	5.75821

According to the statistical results, the data statistics and information supervision are carried out by using the two models of prevention and control information supervision pointed out in the experiment. In addition, in order to improve the market fluctuation, a set of additional financial sequential risk codes are designed and added. The financial risk data are directly inputted into the financial information to ensure market risk access and tail risk. After risk assessment and prediction, the experiment takes boundary cost risk prediction and market arbitrage mechanism measurement as verification objectives. Figure 8 shows the comparison of experimental boundary costs.

According to the information data in Figure 8, it can be clearly seen that after the traditional model and the design model are invested, the boundary cost of the financial market fluctuates significantly. However, as can be seen from the experimental data given, the boundary cost of the traditional model is higher than that of the design model 26.18, 3.4 and 0.95 respectively, which proves that the design model can restrain the marginal cost and resist risks more effectively in risk prevention and control. In order to further verify the experimental conjecture, the experiment took the comparison of market arbitrage mechanism as an auxiliary verification. The comparison results are as shown in Figure 9.

Figure 7 Financial environment information, (a) interbank interest rate (b) negative interest rates (c) income of Shanghai Stock Exchange



Market arbitrage can be regarded as the direct response value of market risk access. The higher the market arbitrage mechanism is, the stronger the market risk is and the easier it is to cause obvious market losses. As can be seen from the two curves in Figure 9, under the influence of the traditional model and the design model, the market arbitrage result fluctuates greatly, but the overall trend is relatively stable. It can be seen from the comparison results that the influence data of applying traditional model on market arbitrage mechanism is significantly higher than that of applying design model.

According to the statistical comparison of the data, it can be determined that it reduces by at least 22%, which proves once again the role of the design model in the prevention and control of financial risks in the market.

Figure 8 Comparison of boundary cost

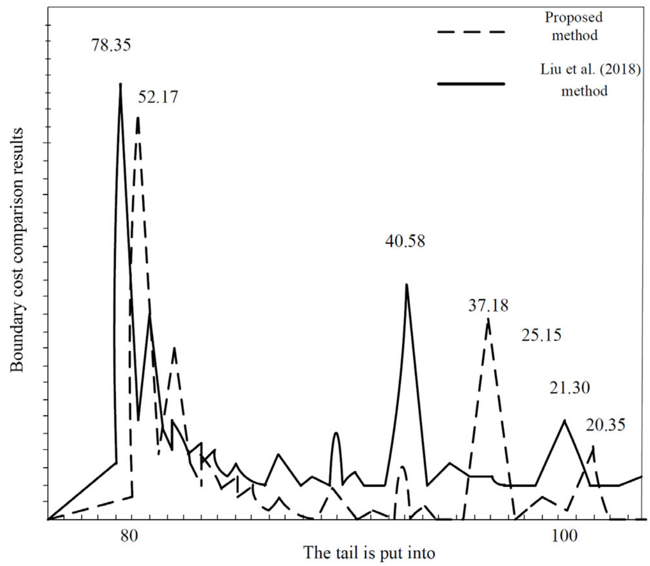
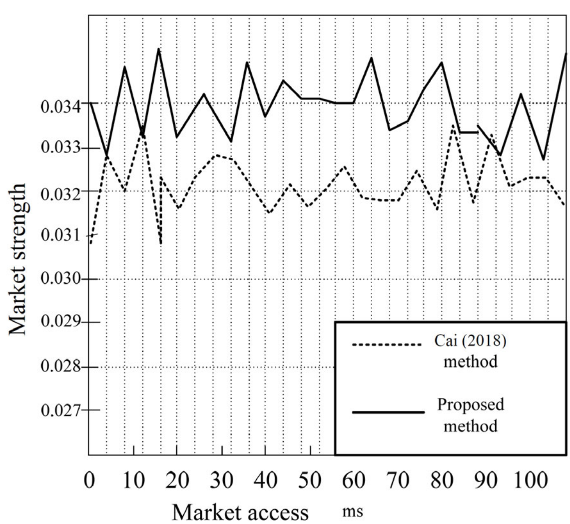


Figure 9 Comparison of market arbitrage mechanisms



4 Conclusions

Finance is an important part of social and economic development. The prevention and control of financial risk information is the core problem of current financial research. Aiming at the problems of poor effect and low accuracy of current financial market risk prevention and control methods, this paper proposes a financial risk prevention and control information monitoring model based on double SVM. Twin SVM is the core computing framework. Through the construction of CoVaR model data set, extreme quantile regression was carried out on the financial data of a bank in March 2019, the financial tail information samples were identified, data decomposition was completed, and the final regulatory estimation results were determined according to the extreme value evaluation of binary POT. Experimental results show that this method can effectively reduce the boundary cost and has a high market arbitrage. Therefore, the financial risk prevention and control information monitoring model proposed in this paper can be well applied to financial risk prevention and control. During the experiment, the experimental environment is different from the real environment due to the setting of the parameters of the experimental environment. The experimental result deviates from the actual result, but it does not affect the experimental conclusion. In order to obtain more accurate experimental results, the proposed method needs to be further optimised and studied.

References

Ameur, H.B., Clark, E., Palma, A.D. et al. (20180 'Preface: risk management decisions and wealth management in financial economics', *Annals of Operations Research*, Vol. 262, No. 2, pp.239–240.

Bonnafous, L., Lall, U. and Siegel, J. (2017) 'An indicator for drought induced financial risk in the mining industry', *Water Resources Research*, Vol. 53, No. 2, pp.1509–1524.

Cai, T. (2018) 'Financial risk management based on functional data analysis', *Journal of Discrete Mathematical Sciences and Cryptography*, Vol. 21, No. 6, pp.1397–1400.

Crisóstomo, R. and Couso, L. (2018) 'Financial density forecasts: a comprehensive comparison of risk-neutral and historical schemes', *Journal of Forecasting*, Vol. 6, No. 4, p.85.

Furlong, C., De, S.S., Gan, K. et al. (2017) 'Risk management, financial evaluation and funding for wastewater and stormwater reuse projects', *Journal of Environmental Management*, Vol. 191, No. 28, p.83.

Gao, H., Mao, S., Huang, W. et al. (2018) 'Applying probabilistic model checking to financial production risk evaluation and control: a case study of Alibaba's Yu'e Bao', *IEEE Transactions on Computational Social Systems*, Vol. 5, No. 3, pp.785–795.

Izadi, M. and Safdarian, A. (2017) 'Financial risk constrained remote controlled switch deployment in distribution networks', *IET Generation Transmission & Distribution*, Vol. 12, No. 7, pp.1547–1553.

Izadi, M. and Safdarian, A. (2018) 'Financial risk evaluation of RCS deployment in distribution systems', *IEEE Systems Journal*, Vol. PP, No. 99, pp.1–10.

Lin, E.M.H., Sun, E.W. and Yu, M.T. (2018) 'Systemic risk, financial markets, and performance of financial institutions', *Annals of Operations Research*, Vol. 262, No. 2, pp.579–603.

Liu, Y., Zhang, L.J., Han, Y.N. et al. (2018) 'Financial credit risk evaluation model of supply chain finance based on particle swarm cooperative optimization algorithm', *Journal of Jilin University (Science Edition)*, Vol. 39, No. 1, pp.119–125.

Meyer, E.S., Characklis, G.W. and Brown, C. (2017) 'Evaluating financial risk management strategies under climate change for hydropower producers on the Great Lakes', *Water Resources Research*, Vol. 53, No. 3, pp.2114–2132.

Partey, S..T, Dakorah, A.D., Zougmoré, R.B. et al. (2018) 'Gender and climate risk management: evidence of climate information use in Ghana', *Climatic Change*, Vol. 51, No. 1, pp.1–15.

Pavão, L.V., Pozo, C., Costa, C.B.B. et al. (2017) 'Financial risks management of heat exchanger networks under uncertain utility costs via multi-objective optimization', *Energy*, p.139.

Pavão, L.V., Pozo, C., Jiménez, L. et al. (2018) 'Financial risk management in heat exchanger networks considering multiple utility sources with uncertain costs', *Industrial & Engineering Chemistry Research*, Vol. 57, No. 30, pp.589–596.

Sharma, D., Prinja, S., Aggarwal, A.K. et al. (2017) 'Out-of-pocket expenditure for hospitalization in Haryana State of India: extent, determinants & financial risk protection', *Indian Journal of Medical Research*, Vol. 146, No. 6, pp.759–767.

Stehlík, M., Helperstorfer, C., Hermann, P. et al. (2017) 'Financial and risk modelling with semicontinuous covariances', *Information Sciences*, Vols. 394–395, No. 59, pp.246–272.

Yong, L. (2018) 'Design a management information system for financial risk control', *Cluster Computing*, Vol. 2, No. 4, pp.1–9.

Zopounidis, C., Doumpos, M. and Kosmidou, K. (2018) 'Preface: analytical models for financial modeling and risk management', *Annals of Operations Research*, Vol. 266, Nos. 1–2, pp.1–4.