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Regression analysis based financial risk assessment algorithm in the context of digital economy

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Abstract Regression models in the context of digital economy play an important role in financial risk assessment. This paper introduces the DY spillover method in TVP-VAR and establishes the time-varying parameter vector autoregressive spillover index model (TVP-VAR-DY) to measure the level of risk spillover. Based on this, the model evaluation index system is constructed to evaluate and analyze the financial risk situation using the regression analysis of support vector machine. Thirty-six financial institutions in the 2012-2021 interval are selected as research objects for empirical analysis. Under the impact of three major events in 2013, 2015 and 2020, the stock returns of financial institutions have obvious clustering characteristics. China's financial risk spillover index keeps fluctuating within the range of 35% to 55% from 2012 to 2021. The financial risk assessment shows that the model regression values in 2017, 2019, 2020 and 2021 are in the interval of [0.3, 0.7], and China's finance is in a high-risk state. 2013, 2014, 2015, 2016 and 2018 are in a low-risk state.

Index Terms regression model, TVP-VAR-DY model, evaluation index, support vector machine, financial risk

I. Introduction

With the rapid development of information technology and the popularization of the Internet, the digital economy as an emerging economic form has gradually attracted people's attention [1], [2]. Digital economy, of is an economic activity that utilizes digital information technology to promote economic growth and development [3]. It covers the application of digital technology, the development of digital industry and the construction of digital ecosystem, which has brought far-reaching impact on the whole economic system [4], [5]. In the context of digital economy, financial risk assessment is of great significance in promoting the good development of economic and financial markets [6].

Financial risk assessment refers to the comprehensive analysis and assessment of financial institutions, financial products or financial markets to determine the risks they may face and their causes, and to provide corresponding countermeasures and recommendations to effectively manage and control the risks to ensure financial stability and security [7]-[10]. Risk assessment is a very important task in the financial industry [11]. In the process of providing financial services and products, financial institutions face many types of risks, such as credit risk, market risk, and operational risk [12], [13]. Only by accurately assessing these risks can appropriate measures be taken to avoid risks and protect the interests of financial institutions and investors [14], [15]. The uncertainty and complexity of financial markets make risk assessment challenging [16]. In order to better assess financial risks, estimation usually uses a combination of qualitative and quantitative methods [17]. Qualitative analysis focuses on the collection and analysis of relevant data to understand the supply and demand situation in the financial market, the behavior and willingness of market participants, and other factors, so as to predict potential risks to a certain extent [18]-[20]. Quantitative analysis, on the other hand, mainly relies on mathematical models and statistical methods to quantitatively measure and assess various risks, the most representative of which are regression analysis methods [21], [22].

This paper combines the time-varying parameter vector autoregression model with the spillover index method based on generalized variance decomposition to construct the TVP-VAR-DY model to examine the risk spillover of banking, insurance, securities and multi-financial industries for time-varying analysis, reflect the evolution of financial risk, and construct the indicators of financial risk measurement. In response to the problem that the multiple regression model cannot solve the problem of small sample learning well, this paper proposes a regression analysis model of SVM. MSE, R2 and correlation coefficient are used to objectively reflect the generalization ability of the trained evaluation model of this paper. Based on the financial risk evaluation index, the SVM-based regression analysis model is used to assess and analyze the financial risk situation in the 2012-2021 interval.

II. Financial risk assessment in the context of the digital economy

With the continuous development and innovation of the financial market, risk assessment has become a very important task for financial institutions and investors. And the rapid development of big data analytics technology has brought new methods and tools to the financial industry for more accurate assessment and management of financial risks. The application of big data analytics can help financial institutions to discover hidden patterns and trends from huge data, provide more accurate prediction and decision-making support, and thus take timely and appropriate risk management measures [23].

Traditional risk assessment methods mainly rely on statistical models and empirical judgment, limited by sample capacity and data quality. However, with the development of big data analytics, financial institutions are able to process massive amounts of financial data and apply machine learning algorithms for modeling and prediction to more accurately identify and assess risks. For example, by monitoring changes in different market factors, such as interest rates and exchange rates, financial institutions can anticipate possible economic downturns or financial market fluctuations and thus take appropriate risk prevention measures.

III. TVP-VAR-DY modeling

Extreme upside and downside risk spillovers between financial markets portray well the asymmetric pattern of extreme risk spillovers and have received more widespread attention. At the same time, there is also asymmetry in the overall volatility spillover in financial markets, i.e., there is a difference between positive and negative volatility spillovers. In terms of characterizing positive (negative) volatility, the sum of squares of returns in financial markets is used to measure "realized volatility", and the "realized volatility" is decomposed into "good" and "bad" fluctuations according to the positive and negative yields. The U.S. stock market has been studied and found that risk spillovers in the stock market as a whole and by industry are asymmetric. Currently, little literature has examined the asymmetric risk spillovers among financial markets in China. The measurement of asymmetric risk spillover among financial markets is important for risk assessment and portfolio diversification strategy formulation.

Vector autoregressive (VAR) econometric models are often used in multivariate time series analysis, and in order to portray the dynamic evolution of risk, this paper establishes a time-varying vector autoregressive model (TVP-VAR) taking into account the time-varying characteristics. At present, there are two main methods to deal with the time-varying problem, one is to use the rolling window method, and the other is to use the time-varying parametric model. For the rolling window method, not only the number of samples in the window period will be lost, but also the selection of window widths lacks a uniform standard, and the window widths based on subjective settings will affect the estimation results. In addition, the rolling window method lacks robustness when estimating high-dimensional variables. The time-varying parameter model can be a good solution to the problem [24].

In this paper, we construct a time-varying parametric vector autoregressive spillover index (TVP-VAR-DY) model for empirical study, which is based on a time-varying variance one covariance structure and allows capturing possible changes in the underlying structure of the data in a more flexible and robust way. Compared to the traditional DY model, the TVP-VAR-DY model has advantages in capturing dynamic changes in time series data, improving model fit, reducing subjective bias, and robustness to outliers, thus making it more suitable for empirical studies of risk spillovers in financial markets [25].

First, the construction process of TVP-VAR-DY model is as follows:

$$x_t = \partial_t x_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, Z_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \mu_t, \mu_t \sim N(0, P_t) \tag{2}$$

In Eq. (1), x_i and x_{t-1} are N × 1 and Np × 1 dimensional vectors, respectively, $\hat{\sigma}_i$ is an N × Np dimensional time-varying parameter matrix, and ε_t is an N × 1 dimensional error perturbation term. In Eq. (2), $vec(\beta_t)$ denotes the N × Np-dimensional time-varying coefficient matrix, and μ_i is an N × Np-dimensional random perturbation term. The generalized impulse response function and the generalized prediction error variance are the basis for estimating the DY spillover index, so the TVP-VAR is converted to TVP-VMA form, denoted as $x_t = \sum_{j=0}^{\infty} A_{jt}\varepsilon_{t-j}$. where A_{jt} is an N × N dimensional matrix.

Secondly, the FEVD matrix is solved, and the matrix element is set to $\theta_i(H)$, where $\theta_{ij}(H)$ means that when the variable x_i is subjected to an external shock, the proportion of the variance of the H-step prediction error of x_i explained by the variable x_i is depicted, and the spillover effect of the variable x_j on x_i is depicted:

$$\theta_{ij}^{H} = \frac{z_{ij}^{-1}\sum_{h=0}^{H-1}(e_i^{'} A_h \sum e_j)^2}{\sum_{h=0}^{H-1}(e_i^{'} A_h \sum A_h e_j)} \tag{3}$$

In the matrix θ^H, the sum of the contributions of x_j to the variance of the prediction errors of the variable x_i is not equal to 1, i.e.: $\sum^{N}\theta_{ij}^{H} \neq 1$. Therefore, it needs to be normalized to:

$$\tilde{\theta}_{ij}^{H} = \frac{\theta_{ij}^{H}}{\sum_{j=1}^{H}\theta_{ij}^{H}} \tag{4}$$

The matrix $\tilde{\theta}^H$ satisfies $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{H} = 1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{H} = N$.

The aggregate spillover index measures the contribution of volatility shock spillovers between financial markets to the total forecast error variance, defined as follows:

$$S(H) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ij}^{H}}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{H}}\times 100 = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ij}^{H}}{N}\times 100 \tag{5}$$

The Directed Spillover Index represents the risk spillover from market i to other markets and the risk spillover from other markets to market i, respectively, as defined below:

$$S_{Fi}(H) = \frac{\sum_{j=1,j\neq j}^{N}\tilde{\theta}_{ij}^{H}}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{H}}\times 100 = \frac{\sum_{j=1,j\neq j}^{N}\tilde{\theta}_{ij}^{H}}{N}\times 100 \tag{6}$$

$$S_{n}(H) = \frac{\sum_{j=1,j\neq j}^{N}\tilde{\theta}_{ij}^{N}}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{N}}\times 100 = \frac{\sum_{j=1,j\neq j}^{N}\tilde{\theta}_{ij}^{N}}{N}\times 100 \tag{7}$$

The net spillover index represents the difference between the total volatility transmitted to other markets and the volatility shocks received from the rest of the market market i The net volatility transmitted to other markets is defined as:

$$S_{Ni}(H) = S_{Ti}(H) - S_{Fi}(H) \tag{8}$$

This study deals with volatility by dividing it into two components: positive and negative volatility. However, this paper does not use high-frequency data to calculate the realized volatility, but uses the daily return data to calculate the weekly volatility, and it is proved that the realized variance converges to the quadratic variance in accordance with the probability, and it is a consistent estimator of the true volatility realized semi-variance model, that is:

$$RV_t = \sum_{i=1}^{5} R_{t,i}^{2} \tag{9}$$

where RV_t is the weekly realized variance and $R_{t,l}^{2}$ is the square of the i daily return for the t th week $(i = 1, 2....,5)$, and the daily return is calculated as $R_t = \ln P_t - \ln P_{t-1}$, is the closing price of the stock on day t. Relative to the method of calculating realized volatility using intraday high-frequency data, this method still suffers from some noise, but it does not deviate much from the actual results, and a consistent fit to the actual volatility can be achieved.

Positive and negative volatilities are calculated by the formulae, respectively:

$$RV_t^+ = \sum_{i=1}^{n_1} R_{t,i}^2 (R_{t,i} > 0) \tag{10}$$

$$RV_t^- = \sum_{i=1}^{n_2} R_{t,i}^2 (R_{t,i} < 0) \tag{11}$$

where n_1 and n_2 are the number of days in a week with positive and negative returns, respectively. By bringing (9)~(11) into (3)~(8) respectively, we can compute the total risk spillover, positive risk spillover (S^+) and negative information spillover (S^-), and also construct the SAM used to measure the asymmetry of risk spillover:

$$SAM = S^+ - S^- \tag{12}$$

When positive risk spillover is greater than negative risk spillover, SAM is greater than 0. Conversely, SAM is less than 0. Meanwhile, this approach can also be applied to study the asymmetry of directional information spillover:

$$SAM_{i\to\cdot} = S_{i\to\cdot}^+ - S_{i\to\cdot}^- \tag{13}$$

$$SAM_{i\leftarrow\cdot} = S_{i\leftarrow\cdot}^+ - S_{i\leftarrow\cdot}^- \tag{14}$$

where $SAM_{i\to\cdot}$ and $SAM_{i\leftarrow\cdot}$ represent asymmetry measures of outward and receiving spillovers, respectively.

IV. Support vector machine regression

IV. A. Multiple regression analysis

For the risk assessment model, previous researchers have used a variety of methods for its modeling research. To synthesize the current situation of risk assessment analysis, one of the more commonly used methods is to use regression analysis to calculate financial risk assessment indicators and their weights.

Multiple regression analysis prediction method refers to the method of establishing a prediction model for prediction by analyzing the correlation between two or more independent variables and a dependent variable. When there is a linear relationship between the independent variables and the dependent variable, it is called multiple linear regression analysis [26].

Let y be the dependent variable, $x_1, x_2, \cdots x_k$ be the independent variables, and when there is a linear relationship between the independent variables and the dependent variable, the multiple linear regression transversal type is:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_k x_k + e \tag{15}$$

where b_0 is a constant term, $b_1, b_2, \cdots b_k$ is the regression coefficient, b_1 is $x_2, x_3 \cdots x_k$ is fixed, and each additional unit of x_1 is the partial regression coefficient of x_1 on y. Parameter estimation for a multiple linear regression model involves solving the values of the parameters $b_0, b_1, b_2, \cdots b_k$ by least squares to obtain the regression equation, provided that the sum of the squared errors (Σe^2) is required to be minimized.

IV. B. Support vector regression model

In view of the support vector machine algorithm can be a good solution to small sample learning, and nonlinear regression can be a good way to overcome the problem of “dimensionality disaster”, therefore, this paper chooses to use the regression model of the support vector machine to realize the construction of the financing risk model.

The principle of support vector regression machine and classification machine is basically similar, the difference is that the regression machine outputs actual values, while the classification machine outputs categories.SVR is different from the traditional regression model, SVR assumes that a spacing band with a width of 2ε is constructed, centered on $f(x)$, and if the sample points fall into the spacing band, it indicates that the values are reasonable [27].

It is known that the training set $X = \{(x_1, y_1), (x_2, y_2), \cdots, (x_i, y_i)\}$, where $x_i \in R^n$ (an n-dimensional space), $y_i \in R$ (set of real numbers), and the function $f(x)$ is a regression function with the following formula:

$$f(x) = w \cdot \Phi(x) + b \tag{16}$$

where w is the weight vector, $\Phi(x)$ is the nonlinear mapping, and b is the bias. Introducing the insensitivity coefficient ε, the penalty factor C, the loss function L_ε, and the slack variables ξ_i, the linear regression problem for the $\xi_i^* \geq 0$ support vector machine can be solved for the regression function by the following equation:

$$\min \frac{1}{2}\|w\|^2 + C\frac{1}{l}\sum_{i=1}^{l}(y_i, f(x_i)) \tag{17}$$

$$s.t.\begin{cases} y_i - w\cdot\Phi(x) - b \le \varepsilon + \xi_i \\ w\cdot\Phi(x) + b - y_i \le \varepsilon + \xi_i \\ \xi_i, \xi_i^* \ge 0 (i = 1,2,\cdots,l) \end{cases} \tag{18}$$

Introducing Lagrange multiplier vectors and Lagrange functions leads to a dyadic form of:

$$\max(a_i, a_i^*) = \frac{1}{2}\sum_{i,j=1}^{l}(a_i - a_i^*)(a_j - a_j^*)K(x_i \cdot x_j) - \sum_{i=1}^{l} a_i(\varepsilon - y_i) - \sum_{i=1}^{l} a_i^*(\varepsilon + y_i) \tag{19}$$

$$s.t.\begin{cases} \sum_{i=1}^{l}(a_i - a_i^*) = 0 \\ 0 \le a_i, a_i^* \le C(i = 1,2,\cdots,l) \end{cases} \tag{20}$$

Further the decision function for support vector machine regression can be obtained:

$$\begin{cases} \max L(\alpha) = \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j (x_i \cdot x_j) \\ s.t. 0 \le \alpha_i \le C, \sum_{i=1}^{l}\alpha_i y_i = 0, i = 1,2,\ldots,l \end{cases} \tag{21}$$

$$f(x) = \sum_{i=1}^{l}(a_i - a_i^*)K(x_i, y_i) + b \tag{22}$$

From the above optimization formula, a_i and a_i^* can be found, and if a_i and a_i^* are not zero, then the corresponding (x_i, y_i) is a support vector.

V. Empirical analysis

V. A. Data description

How to prevent national systemic financial risks is an important part of the financial regulatory reform in major European and American countries in the post-financial crisis era, and it has also been emphasized by the Chinese government in many economic and financial work conferences in recent years. Over the past decades, maintaining financial stability and preventing systemic financial risks have become the main concerns of governments and financial regulators, while the occurrence of the international financial turmoil that swept the world in 2007 prompted countries to pay more attention to the stability of the financial system and its impact on the real economy.

Limited to the availability of data, in consideration of the listing time and the number of days of suspension and other factors, this paper selects 36 listed financial institutions as the object of research, specifically including 14 banks, 10 securities, 4 insurance and 8 multi-financial institutions, the sample interval for the period from January 4, 2012 to June 30, 2021, a total of 36 × 2305 = 82,980 pieces of data, covering The sample period is from January 4, 2012 to June 30, 2021, with a total of 36×2305=82,980 pieces of data, covering important events such as the “Money Shortage” in 2013, the “Stock Market Crash” in 2015, the “Crude Oil Treasure” of Bank of China, and the Xin Guan Epidemic. Compared with financial statement data, stock data is more frequent, and the information it contains is forward-looking and real-time, which can reflect the evolution of financial risks in a timely manner, as shown in Table 1 for specific financial institutions, and the data comes from Wind database.

Firstly it is necessary to calculate the financial institutions stock return, secondly to decompose the stock return and finally to obtain the public and heterogeneous volatility. Firstly, it is necessary to calculate the financial institution stock return, secondly to decompose the stock return, and finally to obtain the public and heterogeneous volatility. Therefore, this paper calculates the logarithmic stock return $r_{it} = \ln(p_{i,t}) - \ln(p_{i,t-1})$, where pi, t refers to the closing price of financial institution i at time t. The data calculated for 36 financial institutions are averaged in the cross-sectional dimension to obtain the financial system return series as shown in Figure 1. As can be seen from Figure 1, the financial system showed obvious agglomeration characteristics under the impact of three major events: the "money shortage" in 2013, the "stock market crash" in 2015 and the new crown epidemic, among which it was obvious during the "stock market crash" in 2015, indicating that it had the greatest impact on the income of the financial system.

Table 1: Financial institution

Serial number	Mechanism	Serial number	Mechanism	Serial number	Mechanism
1	Ping an bank	13	Bank of China	25	China ping an
2	Ningbo bank	14	Citic bank	26	China taibao
3	Pudong bank	15	Northeast securities	27	Chinese longevity
4	Huaxia bank	16	National securities	28	Xinhua insurance
5	Minsheng bank	17	Guangfa securities	29	Shaanxi national investment a
6	China merchants bank	18	Changjiang securities	30	Hyde stock
7	Nanjing bank	19	Citic securities	31	Tomu
8	Societe generale	20	National securities	32	Oriental energy
9	Bank of Beijing	21	Haitong securities	33	Homology
10	Traffic bank	22	Merchants securities	34	Xiangcheng
11	Icbc	23	Pacific securities	35	Huaxin
12	Construction bank	24	Everbright securities	36	Havoting

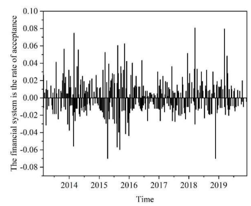

Figure 1: The financial system is the rate of acceptance

The financial institutions' returns are averaged by sector to obtain the average return of the sector, and observing the characteristics of the sectoral data distribution, the results of descriptive statistics of the sectoral returns are shown in Table 2. From the standard deviation column in the table, it can be seen that the securities sector, the insurance sector and the multifinancial sector have relatively large fluctuations, which may be due to the extreme event shocks, and compared with the above three sectors, the banking sector has a more robust performance.

Table 2: descriptive statistics

Industry	Mean	Min	Max	SD	Degree of bias	Kurtosis	Observed value
Bank	-0.0002	-0.0745	0.0884	0.0145	0.8325	10.8563	2300
Securities	-0.0008	-0.1523	0.0956	0.0226	0.1284	9.3247	2300
Insurance	0.0005	-0.1036	0.0946	0.0197	0.5496	7.0415	2300
Diversified finance	-0.0018	-0.1522	0.0952	0.0198	-0.0882	11.8362	2300

V. B. Time-varying analysis of risk spillovers in the financial sector

The TVP-VAR-DY model is now used to conduct a time-varying analysis of risk spillover in four financial sectors in China, and this section proceeds from overall risk spillover to localized spillover. The fluctuation of the risk spillover index is shown in Figure 2, demonstrating that the fluctuation of China's financial risk spillover index ranges from 35% to 55%. Around 2013, 2015 and 2020, the financial risk spillover index increased significantly, indicating that crisis events such as "money shortage", "stock market crash" and the COVID-19 pandemic would impact China's financial industry and intensify financial risks. At the same time, it also proved that the financial risk spillover index calculated through the TVP-VAR model can be used as a measurement indicator of financial risks in China. Effectively depict the time-varying characteristics of financial risks in China.

Specifically, the financial risk premium index was at a high level of 45% to 55% in 2010-2012, probably affected by a series of events such as the previous outbreak of the European debt crisis. After 2012, there was a clear downward trend, and after the impact of the “money shortage” event in 2013, the financial risk premium index rose from about 35% to about 50%, and then declined after 2014. As the management's “deleveraging” in the second half of 2015 caused a sharp shock to the Chinese stock market, resulting in a sharp rise in financial risk, the financial risk premium index was as high as about 55% at this time, and lasted for a long time. At the same time, the outbreak of CKP in early 2020 and its rapid spread globally changed investor expectations and risk appetite, resulting in a strong correction in global equity markets and an increase in financial risk, which caused the spillover index to peak again at about 50 per cent.

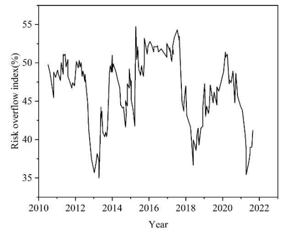

Figure 2: Financial system risk overflow sequence diagram

VI. Study on the Evaluation of Financial Risks in China

The 6,000 samples from the experimental preparation data were randomly divided into 3 groups of 3,600 (60% of training samples), 1,200 (20% of test samples) and 1,200 (20% of test samples). The above 3 groups of data were normalized and the SVM algorithm was used to build the regression analysis model.

In this paper, the SVM regression algorithm is used to construct the early warning model, which utilizes the root mean square error, the mean absolute error and the correlation coefficient of the training samples, test samples and test samples to indicate the index values of the model performance. Table 3 shows the experimental data obtained by the model in the 3 types of data, and from the data analysis, it can be seen that the constructed early warning model is very close to the characterization ability of the 3 types of samples. The performance indicators come as shown in Table 3, the model has a good generalization ability, and its validity and reliability are good.

Table 3: model of the ability indicator

Sample	Mean and mean error	Absolute mean	Correlation coefficient
1	0.894	0.0841	0.986
2	0.912	0.0723	0.985
3	0.922	0.0764	0.970
4	0.915	0.0749	0.968
5	0.920	0.0778	0.969

Macro state variables such as the logarithmic return of the Shanghai Composite Index, volatility, and short-term liquidity example difference are selected as early warning indicators, and financial risk is included in the early warning indicators because financial risk also plays a role in its own early warning. The frequency of early warning variables in this paper is daily, so the monthly, quarterly and annual related data are not considered, and the final constructed early warning indicators are shown in Table 4. Therefore, the construction of the model evaluation indicators in this paper is mainly based on the evaluation method of financial risk indicators, while taking into account the actual situation of the company and the characteristics of the financing risk, and finally selected seven indicators, including financial risk, the logarithmic return of the Shanghai Composite Index (SCI), the daily volatility of the SCI, short-term liquidity spreads, interest rate risk, the term structure of the interest rate, and the real estate yield.

Table 4: China's financial risk warning index

Index name	Index construction
Financial risk (TOT)	Financial risk overflow index based on the financial sector
The benchmark returns on the Shanghai composite index (RE)	Logarithmic return of daily closing price
The Shanghai composite index per day (VO)	The lowest price of the day is the lowest price
Short-term liquidity spreads (SI)	The difference between the six months of shibor and the six-month Treasury interest rate
Interest rate risk (IS)	The difference between the maturity of the six months of debt
Rate term structure (SC)	The difference between the interest rate of the six months of the t period and the 10-year bond interest rate, minus the six months of the t-1 period, the difference between the interest rate of the Treasury and the 10-year Treasury rate

Returns (HR)	Logarithmic return of daily closing price

This paper holds that overly detailed classification of early warning levels will have an impact on the risk indicators synthesized by different algorithms, which is not conducive to the prediction of the decision-making system. Therefore, the early warning level situations are classified according to the "3, 7" standard. The early warning level situations are shown in Table 5, namely four states: severe early warning state, mild early warning attitude, low-risk state, and safe state.

Table 5: Company warning grade division

Warning grade	Warning value
Severe warning state	[0,0.3]
Mild warning state	[0.3,0.7]
Low risk state	[0.7,0.9]
Safe state	[0.9,1.0]

This paper uses the financial data from 2013 to 2021 to construct a regression model, and the model output values obtained are shown in Table 6, with the smaller data indicating a higher financial risk.

The model regression values of 2017, 2019, 2020 and 2021 are all at [0.3, 0.7], indicating that the financial risk is higher, in a “mild warning” state. From the model regression value of these four years into a decreasing trend in recent years, indicating that the financial risk in recent years is increasing, the relevant departments should take some macro-control policies to strengthen the control of financial risk, to prevent it from transforming to the “severe warning” status. By comparing the model predicted risk status and official data, found that the two in the risk of early warning status and risk trends basically coincide, indicating that the analytical model constructed in this paper in predicting the effectiveness of real estate risk.

From the data in the table, it can also be seen that the financial risk model regression value in 2013, 2014, 2015, 2016 and 2018 is [0.7, 0.9], indicating that it is in the state of “low risk status”, and further analyzing the risk data in these four years, it is found that the model regression value is 0.861, which is very good in 2018, and the model regression value is 0.861, which is very good in 2018. Further analyzing the risk data for these four years, it is found that the model regression value for 2018 is 0.861, which is very close to 0.9, so the financial risk for that year is close to the “safe state”.

Table 6: Model regression analysis results and risk rating

Year	Model regression value	Risk level	1 level	2 level	3 level	4 level
2013	0.806	2	1	6	5	3
2014	0.822	2	1	7	4	3
2015	0.856	2	1	5	5	4
2016	0.835	2	1	5	6	3
2017	0.684	3	0	4	6	5
2018	0.861	2	1	4	5	5
2019	0.612	3	0	4	6	5
2020	0.584	3	0	4	6	5
2021	0.571	3	0	3	7	5

VII. Conclusion

This paper analyzes the risk spillover and dynamic evolution of China's four major financial sectors from 2012 to 2021 using the TVP-VAR-DY model in the context of the digital economy and the financial all-industry perspective. Based on the financial risk indicators, a regression analysis model using SVM is used to evaluate the financial risk situation. Empirical analysis shows that China's financial system is characterized by agglomeration under the impact of the “money shortage”, “stock market crash” and the new crown epidemic. 2012-2021 China's financial risk spillover index fluctuates constantly within the range of 35% to 55%. Its spillover index was at a high level from 2010 to 2012. Due to the sharp rise in financial risks in the second half of 2015, which lasted for an extended period of time. The spillover index increased in 2018. At the same time, the outbreak of New Crown Pneumonia in early 2020 raised financial risks and the spillover index almost peaked.

The financial markets were assessed as being in a “low-risk state” for the five years 2013, 2014, 2015, 2016 and 2018, with financial risk approaching a “safe state” in 2018. In the remaining years, financial risks were in “high risk status”.

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