Research Article

Construction of Real Estate Debt Crisis Early Warning Model Based on RBF Neural Network

Gui Jianyu,1 Peng Wenzhi,1 Jiao Mingqing,2 and Zhou Dong3

1School of Management and Economics, Jingdezhen Ceramic University, Jingdezhen 333403, China
2Department of Planning & Financial Affairs, Jingdezhen Ceramic University, Jingdezhen 333403, China
3Institute of Political Science in Sichuan, Academy of Social Sciences, Chengdu 610000, China

Correspondence should be addressed to Peng Wenzhi; pengwenzhi@jcu.edu.cn

Received 24 March 2022; Revised 9 April 2022; Accepted 16 April 2022; Published 7 May 2022

Academic Editor: Muhammad Arif

Copyright © 2022 Gui Jianyu et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The current market economic environment is constantly changing, and real estate companies are constantly facing various risks in the course of their operations, which have created some obstacles to real estate companies’ normal financial activities, and the occurrence of a debt crisis may reduce the company’s expected benefits. If real estate companies can identify debt risks early on and take effective steps to avoid them, they will have a better chance of avoiding debt problems. Therefore, this study introduces RBF neural network technology to construct a new real estate debt crisis early warning model. This study selects 20 indicators, constructs the financial early warning index system of listed companies, collects the financial data of 86 real estate listed companies from 2016 to 2020, uses the principal component analysis method to reduce the dimension of the collected financial data, and uses the reduced dimension data to construct the real estate debt crisis early warning model of RBF neural network to realize the real estate debt crisis early warning. The empirical results show that the early warning model constructed in this study can effectively warn the real estate debt crisis, effectively analyze the development trend of real estate companies, help to better prevent the debt crisis of real estate enterprises, and improve the comprehensive benefits of real estate enterprises.

1. Introduction

In the late 1980s, in the research of financial theory at home and abroad, the research on the impact of financing structure on business performance has gradually become the focus of academic attention. The research on this can be basically divided into two aspects: on the one hand, pay attention to the impact of equity financing structure on business performance, on the other hand, pay attention to the impact of debt financing structure on business performance [1]. Numerous studies, both domestic and international, have shown that the finance structure has a major influence on the company’s operational success. With the maturation of information technology, numerous businesses are speeding up the process of information building, and public financial accounting has shifted from a conventional mode to one based on information and networking. The use of network technology can promote the mutual cooperation between business and financial accounting of public institutions and realize the management and control of remote accounting, financial data accounting, financial audit, and other aspects of financial work [2]. The financial operation mode of public institutions is made to fundamentally change, and the processing speed of financial and accounting information is more efficient and timely. Financial accounting information involves the financial data, operating status, and cash flow of public institutions. It is the most confidential data information of public institutions [3]. With the continuous improvement of the informatization level of public institutions, network technology not only makes the financial accounting treatment of public institutions more convenient and fast but also improves the security risk level, which can include the following aspects.

Firstly, there may be some loopholes in the development of financial accounting software used by public institutions, which may lead to risks in the financial accounting
information of public institutions. Secondly, there are security risks in the remote transmission of financial accounting information. Different from the traditional financial information transmission, the financial accounting information in the process of remote transmission exists in an electronic way and lacks authentication marks such as signature [4]. Therefore, the authenticity of financial accounting information is questioned and its reliability is reduced. Thirdly, electromagnetic interference, hacker attacks, and computer viruses lead to the damage of financial accounting information and the loss of data in the transmission process. Fourthly, nonfinancial personnel use financial software to change financial accounting information without authorization. Therefore, the security of financial accounting information has become the focus of public institutions. The key to information security is information encryption. To realize the safe transmission of financial accounting information, encryption is an important means to ensure the security of financial accounting information of public institutions [5].

When studying the impact of debt financing structure on business performance, domestic and international scholars frequently treat debt as homogeneous, focusing only on the overall debt structure's impact on business performance while ignoring the differences in the impact of different maturities and types of debt on business performance [6]. Different types of debt crises can affect the security of real estate companies, putting strict constraints on management and putting greater strains on cash flow; a long-term enterprise debt problem will affect the normal operation of the company, and the financing cost is high, and the company's management's constraint ability is weak. Therefore, an in-depth study of the impact of real estate debt types on the operating performance of real estate companies is important for the company to establish the optimal debt financing structure and realize the early warning of real estate debt crisis. However, the real estate industry is a typical capital-intensive industry with high risk, high investment, and high return. Its development process is characterized by large capital investment, long investment payback period, weak asset liquidity, and significant impact by macro-policies [7]. Novel coronavirus pneumonia is still in high operation in 2020. Under the impact of the new crown pneumonia, people’s income is reduced, people’s desire to buy is reduced, and real estate enterprises are seriously affected. Therefore, early warning of the real estate debt crisis can effectively enhance the stability of real estate enterprises [8].

Therefore, this study proposes a real estate debt crisis early warning model based on RBF neural network to monitor the operation safety of real estate enterprises.

2. Construction of Real Estate Debt Crisis Early Warning Model Based on RBF Neural Network

2.1. Data Source and Sample Selection. In the CCER China economic and financial database, 910 Shenzhen SME real estate enterprises were selected. After screening according to the value of financing fixed asset expenditure in the enterprise cash flow statement, it can be seen that some enterprises are not financing. Based on the financial data of 910 small- and medium-sized board-listed real estate enterprises, the number of enterprises with financing from 2016 to 2020 is 117 institutes [9]. To warn the debt crisis of real estate companies, this study introduces RBF neural network to build an early warning model and selects listed real estate companies as research samples. The selection of samples needs to meet the following requirements:

1. Select A share real estate listed companies in Shanghai and Shenzhen, and eliminate B shares and H shares;
2. Eliminate ST companies to avoid the impact of special circumstances of such companies [10];
3. Eliminate the companies listed after 2012 to avoid the unstable impact of the company’s initial financing structure on operating performance; and
4. Eliminate companies with incomplete data to ensure the comprehensiveness and stability of data. Based on the above principles, 86 listed real estate companies were selected, and their stock codes and abbreviations are shown in Table 1.

The above 84 listed data are used to study the debt crisis of real estate enterprises.

2.2. Variable Definition. Based on the above, the relevant variables affecting the debt crisis of real estate enterprises are defined as follows:

1. Listing location variables of real estate companies. When the public institution is listed in both A shares and H shares, then $AH = 1$ and, in addition, $AH = 0$.
2. Accounting information quality variable of real estate enterprises: controllable accruals (DACC), can be obtained through Jones model.
3. Financing constraint variable of real estate enterprises: KZ index. The financing constraints of public institutions can be weighed by the KZ index.
4. Variables in real estate company governance: the validity and practicality of corporate governance structures in terms of monitoring and incentive [11] are assessed. The percentage of shares owned by big shareholders is one of the factors in this table. First, the number of boards of directors, the proportion of independent directors, the number of supervisory boards, the share plans of company leaders, and Cons, all are located in the same area as the independent directors. The variables listed above are all the same. Furthermore, the corporation is used as a unit to induce factors [12] and assess the corporate governance score of real estate companies [13].
5. Manipulation variable: this variable includes enterprise size and asset load rate Lev.
2.3. Design of Correlation Variables. For the explanatory variables of real estate enterprises [14], in the quantitative study of the factors affecting the debt crisis of real estate enterprises, the index is set as the ratio of input to output, and the calculation formula is shown as follows:

\[
\text{Financing degree} = \frac{\text{Financing fixed assets}}{\text{Total assets}}. \tag{1}
\]

The amount of fixed assets of real estate enterprises is obtained in the company’s cash flow statement.

Real estate enterprises are explained variables. RBF neural network was used to analyze the debt crisis of real estate enterprises [15], and the calculation formula for the asset-liability ratio of real estate enterprises was obtained as follows:

\[
Z = 0.012Y_1 + 0.014Y_2 + 0.033Y_3 + 0.006Y_4 + 0.999Y_5. \tag{2}
\]

In formula (2), \(Y_1\) represents the ratio of operating cost to total assets of real estate enterprises, \(Y_2\) represents the ratio of retained earnings to total assets of real estate enterprises, and \(Y_3\) represents the ratio of earnings before interest and tax to total assets of real estate enterprises; \(Y_4\) represents the ratio of equity market value to total assets of real estate enterprises, and \(Y_5\) represents the ratio of sales to total assets of real estate enterprises.

When analyzing the debt crisis of real estate enterprises, considering that there are differences in enterprise-scale and financial leverage, which interfere with the analysis accuracy, we use the scale of real estate enterprises, asset-liability ratio, and return on total assets to set the control variables for empirical analysis [16–19]. Table 2 shows the details of variables for real estate enterprises.

2.4. Construction of Real Estate Debt Crisis Early Warning Model Based on RBF Neural Network. To study the real estate debt crisis, the degree of real estate debt is set as the explanatory variable, the \(Z\) value obtained by RBF neural network operation is set as the explanatory variable, and the financial risk is analyzed through the enterprise scale, asset-liability ratio, and return on total assets to set the control variables for empirical analysis [16–19]. Table 2 shows the details of variables for real estate enterprises.
where intercept term and residual term are described as \( b \) and \( g \) in turn; \( y_1, y_2, y_3, \) and \( y_4 \) are the regression coefficient [20].

A real estate debt crisis early warning model is established as the main test to verify that the debt situation of real estate enterprises is affected by the situation of economic regions [21], which is described by the Z score model as follows:

\[
DACC_{i,t} = y_0 + y_1 \text{Treated}_i \times \text{Post}_t + \sum \text{Controls}_{i,t} + \text{Ind}_t + \text{Month}_t + \mu_{i,t},
\]

where the proxy variable is DACC, which reflects the controllable accrued profit of the real estate enterprise. The information quality of the real estate enterprise is inversely proportional to DACC. The virtual proxy variable is Treated, which is used to judge whether the public institution can be classified into the category of debt crisis. When Treated = 1, it means that the real estate enterprise can be classified into the category of debt crisis; otherwise, Treated = 0. Post is a virtual proxy variable [22], which reflects the time node of real estate enterprise liabilities, and Post = 1 represents that the company is included in enterprise liabilities at this time node; otherwise, Post = 0.

Since the real estate debt crisis early warning model can realize the industrial and monthly control of real estate enterprises [23, 24], it is enough to put Treated \times Post cross-multiplication items in the model. When the coefficient is less than 0, the controllable accrued surplus representing real estate enterprises can be reduced through Shanghai Hong Kong stock connect, to improve the quality of financial accounting information. Through the establishment of the triple multiplication model, the verification of all adjustment variables can be realized. In the process of improving the quality of financial accounting information, the influencing factors are described as follows:

\[
DACC_{i,t} = y_0 + y_1 \text{Treated}_i \times \text{Post}_t + y_2 \text{Mod}_{i,t} + y_3 \text{Treated}_i \times \text{Mod}_{i,t} + \mu_{i,t}.
\]

All adjustment variables are Mod. When the coefficient \( \gamma \) is significantly greater than 0, the adjustment variables can be used to replace the adjustment variables in the process of improving the quality of financial accounting information of real estate enterprises. At this time, the hypothesis is verified. When \( \gamma \) is obviously less than 0, the regulatory variable plays a supplementary role.

The goal of a neural network is to fit data optimally, and it is extensively employed in many industries. The learning process lies at the heart of neural networks. Signal forward propagation and error reverse propagation make up the majority of it. The nonlinear approximation is its primary purpose. This nonlinear approximation neural network can do local nonlinear approximation for particular data and global nonlinear approximation. Each of these neural network systems has its unique set of properties. Firstly, all input parameters can affect the output parameters. This type of neural network is called a global approximation neural network. However, there are a lot of data to be processed in the process of actual data fitting and approximation, which will lead to too long calculation time and too slow speed. Relatively speaking, the amount of data processed by the local approximation neural network is much smaller and the learning speed is very fast. The fitting approximation function of local single data to output parameters is called radial basis function (also known as RBF) [25]; as shown in Figure 1, this function was proposed as early as the last century. RBF function is mainly composed of three layers: input layer, hidden layer, and output layer. There is a nonlinear relationship between the input layer and the hidden layer, but the relationship between the hidden layer and the output layer is linear. The hidden layer is not a single structure level, to achieve better data fitting and approximation. The corresponding number of hidden layers can be set according to the actual amount of data input.

The activation function of the RBF neural network can be expressed as follows:

\[
R(x_p - c_i) = \exp\left(\frac{1}{2\sigma^2} \|x_p - c_i\|^2\right),
\]

where radial basis neural network output is as follows:

\[
y_j = \sum_{i=1}^{k} \omega_{ij} \exp\left(\frac{1}{2\sigma^2} \|x_p - c_i\|^2\right), \quad j = 1, 2, \ldots, n.
\]

Because the sample data in this study are small, the batch gradient descent algorithm, namely the BGD algorithm, is selected to optimize the RBF neural network. BGD algorithm has the following advantages: parallel sample data can move towards the orientation of extreme value more efficiently. When the objective function is convex, the BGD algorithm can get the global optimization. The batch gradient descent method is the most original form. It means that all samples are used to update the gradient in each iteration.

The partial derivative of the objective function is as follows:

---

### Table 2: Variable details.

| Variable type | Variable name          | Code | Variable meaning                          |
|---------------|------------------------|------|------------------------------------------|
| Explained     | Z score value          | Z    | Z score model                            |
| Explain       | Financing degree       | R    | Ratio of financing fixed assets to total assets |
|               | Enterprise scale       | Q    | Natural logarithm of total assets         |
| Control       | Asset-liability ratio  | F    | Ratio of total liabilities to total assets |
|               | Return on total assets | C    | Ratio of net profit to average total assets |


where \( i = 1, 2, \ldots, m \) represents the number of samples, \( j = 0, 1 \) represents the number of features, and \( x_0^{(i)} = 1 \). The parameters for each iteration are updated:

\[
\theta_{j+1} = \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} (h(x^{(i)}_j) - y^{(i)}) x_j^{(i)},
\]

(9)

2.5. Analysis of Financial Ratio and Liability Structure.

The funding of real estate businesses is mostly for the purpose of listing. Enterprises need expert help from the sponsor prior to listing to achieve enterprise packaging. In this case, the financial risk of real estate enterprises may be hidden. Such potential risks will be amplified after the enterprise is listed. In serious cases, the enterprise will have a financial crisis. Therefore, to analyze the financial risk characteristics of real estate enterprises before and after financing listing in detail, it is necessary to analyze the financial ratio of real estate enterprises. The details are shown in Table 3.

The data in Table 3 show that the financing degree, enterprise scale, and return on total assets of real estate enterprises have decreased after the listing of enterprises, but the Z value has not changed significantly, and the growth rate of asset-liability ratio is significant. Therefore, this study uses the asset-liability ratio to analyze the potential financial risks of enterprises. Using a small- and medium-sized enterprise listed in 2018 as the research objective, this study analyzes the potential debt crisis before and after the listing of the real estate enterprise.

3. Experiment

3.1. Stratified Contrastive Regression Analysis of Real Estate Enterprises’ Solvency. There are various factors influencing the financing financial risks of real estate enterprises, but the most significant ones are profitability and debt-paying ability, which can be divided into short time and longtime differences. In this study, the ratio of EBIT to debt is used, and the index of solvency in growth time is set to achieve stratification. According to data records, the number of samples for regression analysis in this study is 117, and the median of EBIT debt ratio is 8.01%. Therefore, this median is taken as the sample stratification standard. The 59 samples larger than this median are set as “significant debt-paying ability” group, and the samples smaller than this median are set as “nonsignificant debt-paying ability” group. The hierarchical comparative regression analysis results of solvency are shown in Table 4.

According to the data in the above table, the average level of Z value of the significant solvency group of real estate enterprises is greater than that of the nonsignificant solvency group, the financial risk of the significant solvency group is small, and the solvency of real estate enterprises is significant, which will reduce the debt crisis risk of real estate enterprises.

3.2. Analysis Results of Financial Ratio and Liability Structure.

The analysis results of financial ratio and liability structure of real estate enterprises after financing and listing are shown in Table 5.

The data in Table 5 show that before the financing listing of real estate enterprises, the average asset-liability ratio is greater than that after the financing listing. After the financing listing, the asset-liability ratio of most enterprises is less than 20%, and the liabilities greater than 92% of the total liabilities are current liabilities. The interest rate on short-term obligations is very unclear, and there are numerous short-term liabilities, implying that real estate firms do not fully use financial leverage, and the payback duration of current liabilities is lengthy, necessitating the reorganisation of cash flow. In this situation, the company is under a lot of debt, there is a lot of danger of capital flow disruption, and there is a lot of risk of a financial catastrophe.
Therefore, real estate enterprises need to reasonably plan the debt structure, increase the proportion of long-term debt, and reduce the financial risk through reasonable financing channels.

3.3. Analysis of Comprehensive Financial Risk Early Warning Results. Through the financial risk early warning model of X Real Estate Company constructed in this study, the financial risk early warning value of X Real Estate Company is calculated according to the process. The financial risk early warning score and corresponding alarm value of X Real Estate Company from 2016 to 2020 are shown in Table 6.

After obtaining the financial risk alarm value of X Real Estate Company, only the value is difficult to directly see the change trend of financial risk of X Real Estate Company. Therefore, to more intuitively see the change trend of financial risk alarm of X Real Estate Company in recent five years, this study analyzes the trend chart of debt crisis early warning evaluation value of X real estate enterprise.

As can be seen from Figure 2, in 2016, the financial risk alarm value score of X Real Estate Company was 0.74, the financial risk was in a light alarm state, and there was a slight financial risk; in 2017, the financial risk alarm value score of X Real Estate Company was 0.43, indicating that there were major problems and obvious decline in financial risk in this year (2017). Combined with the financial situation of the company in that year, it was found that X Real Estate Company changed the existing development strategic plan, upgraded the company’s business, and updated the production process. However, the upgrading plan led to problems in the coordination between the management and confusion in the implementation of the company’s strategy, which led to the deviation in the business decision-making of X Real Estate Company. In 2017, the chairman of X Real Estate Company changed and the business strategic plan of X Real Estate Company changed, so the company’s financial risk increased compared with the previous year; in 2018, the financial risk alarm value score of X Real Estate Company was 0.62, and the financial risk was in the state of medium alarm. Although it was improved compared with the previous year, there were still large financial risks. In 2018, X Real Estate Company tried to obtain more profits by expanding sales channels, and it also tried to change the problem of chaotic financial management of X Real Estate Company since 2017 by changing the marketing strategy, reformed the existing distribution mode, updated the dealer system originally adopted by X Real Estate Company into an agent system through internal management reform, and correspondingly increased the credit line in consideration of the power autonomy of the agent. Although this change has improved the company’s sales, this measure has directly led to a large increase in the financial accounts receivable of X Real Estate Company, and such accounts receivable are difficult to recover, which is bound to lead to loopholes in the normal cash flow of X Real Estate Company, and the vacancy of loopholes will lead to financial risks. By 2019, the early warning value of X Real Estate Company will become 0.45, and the financial risk will further increase. The financial risk is in the state of heavy alarm, and there are significant financial risks. This is because X Real Estate Company first received the image of milk powder product quality problems in 2019, which greatly reduced the social image of X Real Estate Company and led to a crisis of consumer trust. The sales volume of X Real Estate Company decreased and its operating revenue decreased. To alleviate this situation, X Real Estate Company tried to increase its sales by holding sales activities, such as discount sales. However, in this way, the average price of X Real Estate Company’s products decreased and the profits obtained decreased. As mentioned above, X Real Estate Company has adopted the agent model. The reduction in the average price of products has led to the reduction in the agent’s profit, the reduction in profit, and the lack of willingness to sell, which has led to the backlog of housing inventory, the decline of the main business income of X Real Estate Company, and the huge loss of the company. Compared with 2019, X Real Estate Company’s financial risk alarm in 2020 still has significant financial risks. In that year,
the financial risk alarm value score is 0.40, and the financial risk is in the state of heavy alarm, which has significant risks. To reduce losses and obtain sufficient cash flow required for operation, X Real Estate Company chose to sell several properties to offset its debts by exchanging funds and obtain the cash flow required for operation and production. However, X Real Estate Company did not get rid of the existing difficulties. At the same time, the competition in the real estate market is becoming more and more fierce. To expand the free market share, various manufacturers have fought a price war. Therefore, the gross profit margin of X Real Estate Company’s products has been greatly reduced. At the same time, it has also invested a large amount of sales expenses, which has seriously reduced the year-end profit of X Real Estate Company.

4. Conclusion

Economic globalization now not only provides an opportunity for growth, but also introduces a number of unknown elements. The business environment for the corporation is getting more complicated, with growth potential and threats coexisting. If a real estate firm fails to provide timely notice of a financial issue, it will have a significant negative influence on the company, and in severe situations, it may go bankrupt. This study designs a real estate debt crisis early warning model based on RBF neural network. This study selects multiple indicators according to many influencing factors and constructs the financial early warning index system of listed companies. This study collects the effective financial data of 86 real estate listed companies from 2016 to 2020, uses the principal component analysis method to reduce the dimension of the collected financial data, and constructs the real estate debt crisis early warning model of RBF neural network, and the real estate debt crisis early warning based on RBF neural network is realized. The experimental results show that the early warning model constructed in this study can effectively early warn the real estate debt crisis and effectively analyze the development trend of real estate companies. At the same time, real estate enterprises need to reasonably plan the debt structure, increase the proportion of long-term debt, and reduce the financial risk through reasonable financing channels.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] L. Yang and H. Chen, “Fault diagnosis of gearbox based on RBF-PF and particle swarm optimization wavelet neural network,” Neural Computing & Applications, vol. 17, no. 42, pp. 42–56, 2019.
[2] Y. Liu and H. Zhang, "Adaptive RBF neural network based on sliding mode controller for active power filter," International Journal of Power Electronics, vol. 11, no. 4, pp. 460–477, 2020.
[3] F. Liang, Y. Hang, H. Yu, and J. Gao, “Identification of gas-liquid two-phase flow patterns in a horizontal pipe based on ultrasonic echoes and RBF neural network,” Flow Measurement and Instrumentation, vol. 20, no. 2, pp. 961–975, 2021.
[4] H. Zhao, Z. Liu, X. Yao, and Q. Yang, “A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach,” Information Processing & Management, vol. 58, no. 5, Article ID 102656, 2021.

[5] D. Coates, P. Daly, E. Keenan, K. Gerard, and M. Barra, “Who invests in the Irish commercial real estate market?: an overview of non-bank institutional ownership of Irish CRE,” Financial Stability Notes, vol. 12, no. 46, pp. 76–88, 2019.

[6] M. R. Bernardo and C. H. Campani, “Liability driven investment with alternative assets: evidence from Brazil,” Emerging Markets Review, vol. 41, no. 32, pp. 630–653, 2019.

[7] P. Min, “Alternatives to traditional mortgage financing in residential real estate: rent to own and contract for deed sales,” Quarterly Journal of Forestry, vol. 13, no. 43, pp. 215–237, 2020.

[8] H. Zeng and S. U. Qing, “An NK model and fitness landscape-based study of the adaptability of the crisis management system for real estate enterprises,” Journal of Wuyi University(Natural Science Edition), vol. 12, no. 21, pp. 662–678, 2019.

[9] G. J. M. Ruins, “A visual motif of the Spanish real estate crisis (ENG/CAT),” Comparative Cinema, vol. 7, no. 12, pp. 53–68, 2019.

[10] P. Clarkson, “How financial institutions can make their commercial real estate portfolios crisis-proof,” ABA Banking Journal, vol. 112, no. 21, pp. 32–52, 2020.

[11] L. Arnemann, A. K. Kai, and N. Potrafke, “Collective memories on the 2010 European debt crisis,” SSRN Electronic Journal, vol. 12, no. 233, pp. 45–57, 2021.

[12] N. Silva, “Information transmission between stock and bond markets during the Eurozone debt crisis: evidence from industry returns,” Revista Espanola de Financiacion y Contabilidad, vol. 13, no. 2, pp. 43–57, 2020.

[13] V. Swamy, “Macroeconomic impact of eurozone debt crisis on India,” World Economics, vol. 21, no. 16, pp. 69–78, 2020.

[14] G. Economides, D. Papageorgiou, and A. Philippopoulos, “Macroeconomic policy lessons for Greece from the debt crisis,” CESifo Working Paper Series, vol. 12, no. 46, pp. 786–798, 2020.

[15] V. Derenko and S. Yakubovskiy, “Development of financial systems of southern europe countries after the debt crisis,” Market Infrastructure, vol. 16, no. 48, pp. 656–673, 2020.

[16] J. J. Zhang, “Analysis of debt carrying capacity of listed real estate companies based on factor analysis,” Commercial Accounting, vol. 28, no. 12, pp. 43–46, 2019.

[17] A. N. Zker, “The debt crisis phenomenon in the euro area, and its probable financial vulnerability risks,” in Proceedings of the International European Conference on Interdisciplinary Scientific Researches, Ankara, Turkey, July 2020.

[18] P. Handegard, “From crisis to organizational loss of legitimacy—a case study of the European commission during the European debt crisis,” Nanfang Lunkan, vol. 126, no. 32, pp. 76–85, 2020.

[19] D. Oscar, “Sovereign debt crisis and capital structure decisions of firms in GIPSI countries,” African Journal of Business Management, vol. 14, no. 10, pp. 313–323, 2020.

[20] H. S. D. Jiang, “Simulation tools and techniques,” in Proceedings of the 12th EAI International Conference, SIMUtools 2020, Guiyang, China, August 2020.

[21] S. Oger, Made in Spain or Made in Europe? the Roots of Spanish Citizens’ Dismay at the Handling of the Sovereign Debt crisis, Council of European Studies, New York, NY, USA, 2019.

[22] N. Papadopoulos, “Austerity-based labour market reforms in greece v. fundamental rights in the aftermath of the European debt crisis: an analysis of supranational and national bodies’ jurisprudence,” European Public Law, vol. 165, no. 42, pp. 765–781, 2020.

[23] D. Melemeni, K. Mantzouranis, V. E. Georgakopoulou et al., “Depression, anxiety and quality of life in greek hospital staff: a study in the aftermath of the debt crisis era,” Acta Medica Lituanica, vol. 28, no. 2, pp. 220–229, 2021.

[24] E. Emma, “The intellectual, the merchant, and the patriarch: flawed archetypes behind greek government-debt crisis And what we can learn from them in,” Coronavirus Era, vol. 18, no. 48, pp. 160–179, 2020.

[25] T. R. Yan, D. Wang, and L. Z. Xiao, “Simulation of public opinion trend prediction model based on AR-RBF,” Computer Simulation, vol. 38, no. 4, pp. 5–11, 2017.