Establishment of business risk information value assessment model based on RAROC

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Abstract: Aiming at the problem of low precision of current enterprise risk assessment methods, a RAROC based enterprise risk information value assessment model is proposed. The crawler search method with topic search is adopted to collect the business information data, and the extended tree structure is introduced to clean up the collected data, transformation of basic information data and business value. RAROC is used to process the information with commercial value and realise the value evaluation of commercial risk information. According to the model and KMV model, the risk adjustment coefficient was calculated. The results of the RAROC value evaluation are reflected through statements. The experimental results show that the goodness of fit index, standard fit index and comparison fit index of the model are all close to 1, and the approximate root-mean-square error is less than 0.02, which proves the effectiveness and accuracy of the method.

Keywords: RAROC; business risk; assessment; model.

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1 Introduction

Increasingly expose the various risks hidden behind the assets of enterprises, arousing the focus of relevant personnel on the value of information within the company. In addition, in 2007, the success of the reform of non-tradable shares in China's capital market and the rapid expansion of new issuance scale and new investors, as well as the continuous improvement of asset pricing, have led to the diversification of business risks faced by Chinese companies, thus, both corporate managers and relevant government departments. More and more attention has been paid to the comprehensive understanding and management of risks (Wang and Ruan, 2018).

After China's entry into WTO, the major enterprises of our country will face various commercial risks when they enter the competition of the world financial market. In addition, with the outbreak of financial crisis, the public has gradually realised that the comprehensive performance of risk management has become a key component of the comprehensive competitiveness of enterprises (Ning et al., 2016). Under the background of the close connection between China's capital market and the opening up to the outside world, the previous value evaluation models can no longer accurately reflect the business risks existing in the company, so it is urgent to put forward more efficient business risk information value evaluation methods.

Gritzalis et al. (2018) propose a business risk information value evaluation model based on compromise rate method. The weights of evaluation indicators are obtained by calculating the weights by distance measure. The weights of decision makers under the consistency of mutual evaluation and group opinion are constructed. The order of information risk is achieved by compromise rate method. This method can be used for business. The value of risk information is evaluated, but its accuracy is poor. Choi et al. (2016) propose a business risk information value evaluation model based on Jarrow method, which implements the introduction of high-order moment risk into CCA model, collects a series of financial data of 15 commercial banks in China, and calculates the volatility and default distance of implied asset value. This method can accurately measure the systemic risk, but it has great limitations and its application is not ideal. Ehrenfeld and Fleischut (2017) propose a business risk information value evaluation model based on Rudd method. Starting from the micro level, SMOTE algorithm is used to process the unbalanced data. Then, random forest method is used to assign and screen the importance of 20 related variables. Meanwhile, important degree variables are described and analysed. After that, the Logistic model is constructed to evaluate the value of business risk information. Through research and analysis, this method can only provide guidance for business risk early warning and prevention, but lacks the support of scientific data.

Because the current method does not quote the crawler search method with topic search to collect business information data, the accuracy of business risk value evaluation method is poor. In order to solve the problems of current methods, realise the effective evaluation of business risk value, introduce the extended tree structure, and at the same time benefit. The RAROC is used to complete the effective evaluation of business risk value, and the RAROC-based business risk information value evaluation model is proposed. The specific steps are as follows:

1 Introduced the importance of business risk value assessment for the development of enterprises, and briefly described the problems of poor accuracy of current business risk value assessment methods.

2 Collect business information data by crawler search method with topic search, and clean the collected data with extended tree structure. The basic information data and commercial value are transformed to make the collected data have more commercial value.

3 Using RAROC to evaluate the value of business risk information, calculating the risk adjustment coefficient through VaR model and KMV model, realising the risk adjustment of net assets, and then using the report forms to reflect the results of value evaluation;

4 Comparing the goodness of fit index, standard fitting index, comparison fitting index and approximate root mean square error of different methods.

5 Conclusions.

2 Business risk information value assessment

2.1 Business risk information collection

Business risk information value assessment is based on relevant data sets in this field, so as to obtain more accurate evaluation results. According to the specific analysis of specific projects, the crawler search method with topic search is used to realise data acquisition (Lin et al., 2018).

Distributed platform is used to collect business risk assessment related information data. The platform integrates distributed stream computing structure storm and distributed storage HBase with high-speed write-read redis and integrates them into a unified research and development platform. In the process of data acquisition, data acquisition is realised by using storm operation, and the collected results are stored in hbase, and then the clustering results are stored in Oracle database.

In the process of data acquisition using crawlers, the following contents are included:

1 Add data acquisition task queue of business risk assessment related information: when users enter the acquisition mode, add data acquisition task queue for classifying different data acquisition rules.

2 Update the acquisition task queue: When the user enters the acquisition mode, update the acquisition task queue for classifying different data acquisition rules.

3 Delete the acquisition task queue: when the user enters the acquisition mode, delete the task queue to cancel the queue acquisition rules.

4 Add data acquisition tasks related to business risk assessment: when users enter the acquisition mode, in order to expand data sources, add new data acquisition tasks.

5 Update the acquisition task: When the user enters the acquisition mode, in order to change the rules of data acquisition, update the data acquisition task.

6 Delete the acquisition task: when the user enters the acquisition mode, in order to cancel a data source, the data acquisition task is deleted.

7 Transfer data acquisition tasks: when users enter the acquisition mode, in order to change the status of the task queue, transfer data acquisition tasks.

8 Add new information extraction rules for acquisition tasks: when users enter the acquisition mode, configure information extraction rules for acquisition tasks.

9 Change the rules of information extraction about acquisition tasks: when users enter the acquisition mode, modify the data acquisition tasks accordingly.

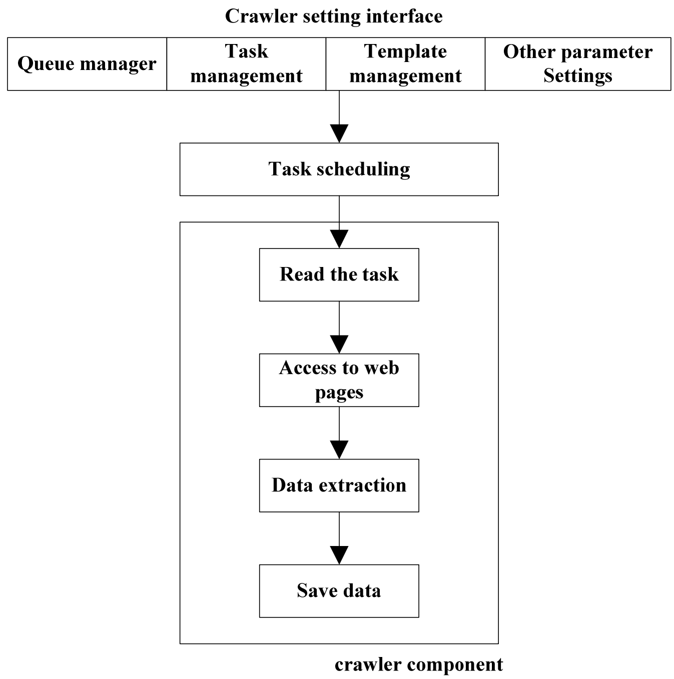
10 Delete the information extraction rules about the acquisition task: when the user enters the acquisition mode, in order to cancel a data acquisition rule, delete the information extraction rules about the acquisition task.

11 Data acquisition: acquisition tasks, data acquisition based on task assignment.

12 Data preservation.

The sketch of the crawler's operation is shown in Figure 1.

Figure 1 Schematic diagram of crawler operation



Data acquisition and data extraction are the key parts of business risk information acquisition (Gao et al., 2017). The business logic of the acquisition component is that the acquisition component receives the task given by the upstream component, assembles the required parameters control, and then processes the data address in standard format to obtain the source code coding rules. If the source code is in conformity with the unified coding form, then it will not be processed, instead, it will be converted into the unified coding standard. After that, the correctly coded web page source is standardised, and finally the processed web page source is transferred to the next component for corresponding processing. The business logic of data extraction is that the extraction component transforms the scattered result data into standard result data based on formula rules (Zhao and Ding, 2018). There are data containers in the formula. Paging information and source information can be added to the data containers. The function in the formula uses the corresponding variables to locate the target data and realise data extraction and assembly. Therefore, it is necessary to set up a data extraction rule template to realise flexible data extraction.

2.2 Data processing of business risk information

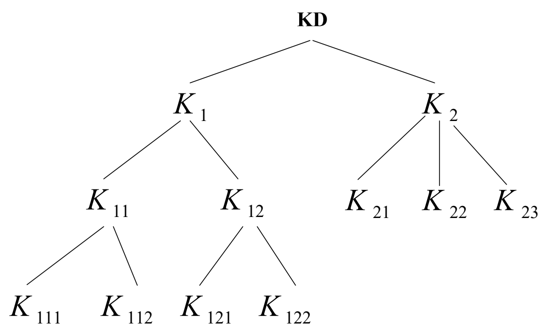
Based on the above data acquisition, this paper introduces the extended tree structure, and according to this structure gives the relevant data cleaning process (Wu and Gu, 2018).

In the practical application process, the relationship between information data is mainly linear and tree structure.

1 Linear structure: Each information data is located at the same conceptual level, and can be cleaned by direct selection.

2 Tree structure: There are hierarchical correlations between information and data on conceptual issues. Each child node has only one parent node, and the child node corresponds to specific information examples. These leaf nodes are defined as 'atomic knowledge', that is, knowledge that can no longer be decomposed and non-leaf nodes correspond only to knowledge concepts (Liu, 2018; Shi and Ye 2016; Ma et al., 2017). As shown in Figure 5, KD represents root node, K_{111}, K_{112} and K_{121} are leaf nodes. In the process of selecting a non-leaf node for processing, it needs to be converted into leaf node for processing.

Figure 2 Example of a tree structure



In the field of data cleaning, it is generally hoped that different knowledge can be selected flexibly and independently for different data to complete the cleaning. At the same time, users at different levels will have different cleaning methods. Based on tree structure, this paper describes knowledge through extended tree structure, which is similar to tree structure, but different from tree structure, each child node can have more than one parent node (Liu, 2018; Shi and Ye, 2016). As shown in Figure 6, there are two parent nodes in node K_{112}: K_{11} and K_{12}, which can be understood as knowledge K_{11} and K_{12} both contain atomic knowledge K_{112}. The expressions of K_{11}, K_{12} and K_{11}, K_1 are as follows:

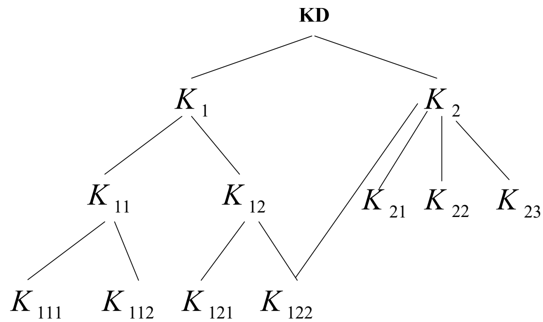
$$K_{11} = \{K_{111}, K_{112}\} \tag{1}$$

$$K_{12} = \{K_{112}, K_{121}, K_{122}\} \tag{2}$$

$$K_1 = \{K_{11}, K_{12}\} \tag{3}$$

In addition, each atomic knowledge is accompanied by a weight value, which is applied to mark the impact of the use of the knowledge on the whole process of data cleaning. The weight determines the order of use in the cleaning process.

Figure 3 Example of an extended tree structure



To sum up, the process of knowledge base construction is as follows:

1 acquiring original knowledge

2 decomposition of primitive knowledge

3 designing and constructing knowledge base

4 setting corresponding weights.

There are differences in the knowledge used by different data in the cleaning process, and they need to be able to choose independently. The cleaning process can be expressed as: based on the user's application to obtain the set of atomic knowledge corresponding to the knowledge, optimise the set of atomic knowledge, get the sequence of atomic knowledge needed in the cleaning process, that is, the cleaning sequence, and finally realise data cleaning according to the sequence (Ma et al., 2017). Detailed steps are as follows:

Input is defined as: Business risk information database, knowledge base

Output is defined as: cleaning the database

1 Selection of cleaning objects

   Assuming that the data attribute set to be cleaned is $\{A_1, \ldots, A_n\}$, the knowledge selected in the knowledge base is $\{RS_1, \ldots, RS_n\}$, and the attributes correspond to the knowledge set (A_i, RS_i).

   The knowledge set $RS_i = \{R_{i1}, \ldots, R_{im}\}$, in which R_{ij} represents non-leaf nodes in the extended tree knowledge base. For each (A_i, RS_i), step (2) operation is performed.

2 Generating atomic knowledge set

   For each knowledge in RS_i, the knowledge base is traversed and all its atomic knowledge is obtained. $R_{ij} = \{R_{ij1}, \ldots, R_{ijp}\}$ and R_{ijk} describe atomic knowledge. Continue step (3).

3 Elimination of repetitive atomic knowledge

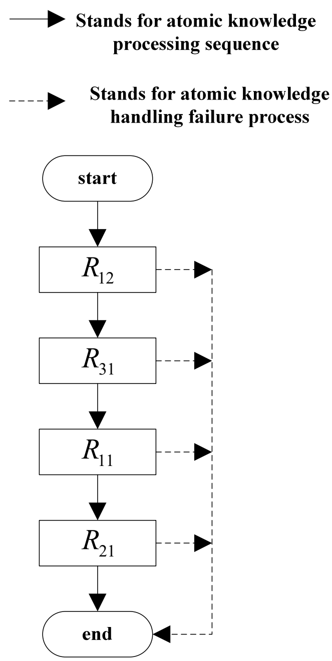
$$RS_i = \{R_{i1}, ..., R_{im}\} = \{R_{i11}, R_{i12}, ..., R_{i21}, R_{i22}, ..., R_{im1}, R_{im2}\} \tag{4}$$

4 Generating atomic knowledge sequence

In the whole data cleaning process, different knowledge processing time is different, so each knowledge corresponds to a processing weight. For the set of atomic knowledge generated in step 3, the sequence of atomic knowledge is obtained by arranging the weight values from large to small.

If there are attributes A and the weight values of atomic knowledge are arranged from large to small and the results are R_{12}, R_{31}, R_{11} and R_{21}, then the corresponding sequence of atomic knowledge corresponding to attribute A can be expressed as (R_{12}, R_{31}, R_{11}, R_{21}). As shown in Figure 4:

Figure 4 Atomic knowledge processing

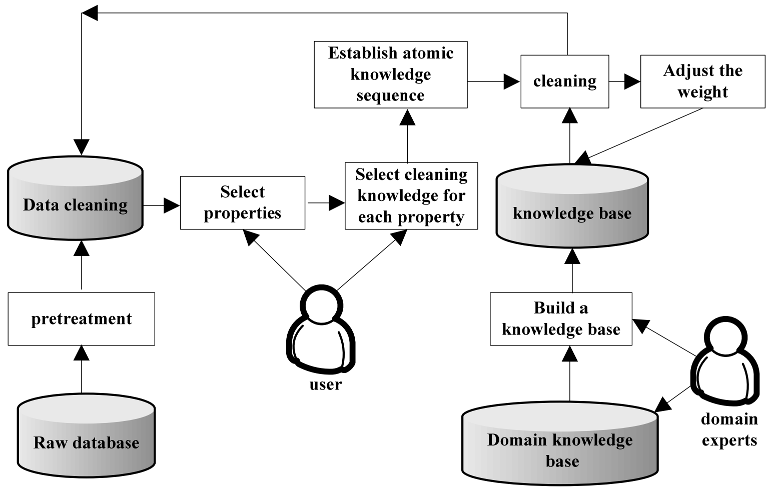


5 Data cleaning based on atomic knowledge sequence

Setting the size of the original database to D and K to represent the length of the atomic knowledge sequence, that is, the number of atomic knowledge in the sequence, the time complexity of the cleaning process is O(D * K).

Figure 5 describes a data cleaning architecture for business risk information based on an extended tree knowledge base (Li et al., 2017a). For users, there are two tasks: one is to select the data attributes to be cleaned the other is to select the knowledge used in the cleaning process, that is, the nodes in the tree structure. For domain experts, there are two tasks, one is to give the corresponding domain knowledge, and the other is to provide appropriate guidance in the process of decomposition and reorganisation of knowledge to build a knowledge base (Luo et al., 2017).

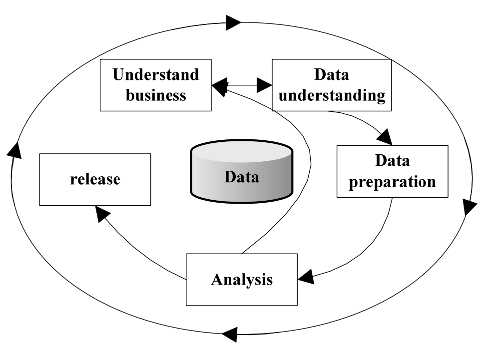
Figure 5 Business risk information data cleaning architecture based on extended tree knowledge base



2.3 *Value assessment of business risk information based on RAROC*

According to the collection and cleaning of business risk information, RAROC is used to realise the value evaluation of business risk information. Before evaluation, the above basic information data and business value are transformed (Li et al., 2017b). Among them, mining information data patterns based on simple analysis and further analysis in cleaning can provide a basis for decision-making of commercial companies, which is a transformation between basic information data and business value, as shown in Figure 6:

Figure 6 Schematic diagram of the transformation between basic information data and business value



Based on the transformation between basic information data and business value, the collected data will have more business value, and the evaluation results will be more accurate.

The ultimate goal of business risk information value assessment is to provide a scientific basis for decision-making with stakeholders. Taking interest as the index of value assessment alone will lead to the problem of excessive risk-taking. Taking risk as the index of value assessment alone will also lead to the problem of over-conservative investment (Dai, 2018; Liu, 2016). In the process of using RAROC to evaluate the value of business risk information, on the basis of weighing the above two, we get the capital support needed by unit income. The expression is as follows:

$$\text{RAROC} = \frac{\text{Net profit}}{\text{Economic capital}} = \frac{\text{Net profit}}{\text{Net assets} * (1 \pm \eta)} \tag{5}$$

In the formula, net profit and net assets are account items in financial statements. η represents the adjustment coefficient of risk. The greater the value, the greater the business risk. When net profit is positive, the value is '+' while the opposite is '–'.

The main idea of RAROC operation is to transform the company's current potential risk, i.e., the unexpected loss risk, into a risk adjustment coefficient by using the advanced computing model, to adjust the company's net assets accordingly, and to obtain the actual capital demand that needs to cover these unexpected loss risks. Because the company anticipates loss risk can be deducted from current profits by using various reserves, the risk has been covered, but the potential risk faced by the company has not been thoroughly solved (Dai and Tao, 2016). RAROC value evaluation method uses molecular coverage of expected loss risk and denominator coverage of unexpected loss risk to obtain the actual intrinsic value of the company after risk adjustment. To sum up, the essence of RAROC operation is to use risk adjustment coefficient to evaluate the efficiency of economic capital use, so as to maximise corporate income (Lu et al., 2017).

In the application of RAROC valuation method, commercial risk consists of market risk and credit risk. The following are calculated one by one to obtain the final evaluation results.

2.3.1 Market risk

Currently, the main methods of market risk measurement are VaR, volatility analysis and stress testing. However, VaR is the most mainstream measurement method. It describes the maximum benefit loss that may be faced within a certain confidence level and holding period. The expression is as follows:

$$\text{Prob}\left(\Delta L_t > \text{VaR}\right) = 1 - \alpha \tag{6}$$

In the formula, VaR represents the value at risk under the set confidence level α, and ΔL_t represents the asset market value variable.

To sum up, VaR has three elements: the size of confidence level, the length of holding period, and the overall distribution characteristics of asset value function.

Assuming that W_0 represents the initial investment, W represents the value of assets at the end of the period, R^* represents the rate of return on investment during the calculation period, and W follows the probability distribution f(w), the relationship between α and the minimum value w^* of assets at the confidence level can be expressed as follows:

$$\alpha = \int_{w^*}^{\infty} f(w)dw \tag{7}$$

The VaR expression is:

$$\text{VaR} = E(W) - w^* = -W_0\left(R^* - \mu\right) \tag{8}$$

Assuming that f(w) is a normal distribution, VaR can be converted to:

$$\text{VaR} = -W_0\left(R^* - \mu\right) = W_0\alpha\sigma\sqrt{\Delta_t} \tag{9}$$

Among them, w^* corresponds to R^{**}, μ and σ represent the mean and variance of R^* and Δ_t represent the time interval.

According to many proofs, the market return sequence usually does not obey the normal distribution and is prone to 'peak and heavy tail'. In view of this situation, a semi-parametric method is introduced to construct the confidence interval of VaR, and the market risk value R * T can be expressed as follows:

$$R * T = -\frac{\text{VaR}_L}{L} \tag{10}$$

In the formula, VaR_L represents the lower limit of the confidence interval, which is the amount of the maximum possible loss at risk, L represents the length of the confidence interval, and the distance between the upper and lower limits of the confidence interval. The theoretical maximum possible risk rate can be obtained by dividing the lower limit of the confidence interval by the length of the confidence interval. Because the lower limit of the confidence interval is negative, so market risk is negative again (Wang and Mei, 2016).

2.3.2 Credit risk

The KMV model is used to calculate credit risk. The default distance DD is used to represent the distance between the expected value of market value V^* and the default point DPT. The smaller the distance is, the greater the possibility of default on behalf of the company is, otherwise the smaller the default distance is. Because DD is a standardised index, it is very helpful to compare different companies in different time periods. The expression is as follows:

$$DD = \frac{V^* - DPT}{V^* \times \sigma_{V^*}} \tag{11}$$

In the formula, σ_{V^*} represents the volatility of asset value.

KMV model is based on the structural relationship between the market value of company's assets and the market value of its equity. The volatility of the market value of company's assets is obtained by historical data, and then the next market value of company's assets is deduced, and the theoretical credit risk is judged (Wang, 2017). In formula (11), σ_{V^*} and V^* are obtained by using BSM option pricing expressions.

$$V_E^* = f\left(V^*, \sigma_{V^*}, r, u, \tau\right) \tag{12}$$

In addition, the relationship between asset value volatility and equity value volatility is introduced.

$$\sigma_E = \frac{V^* N(d)}{V_E^*} \sigma_{V^*} \tag{13}$$

Through simultaneous equations (12) and (13), the market value and volatility of assets can be obtained. R represents the face value of debt, T represents the maturity of debt repayment, U represents the risk-free rate of return, and $N(\cdot)$ represents the standard normal cumulative function.

Based on the above calculation and related research, it can be concluded that the relationship between asset value and normal distribution is obedient, and the theoretical expected default rate EDF can be calculated.

$$EDF = N(-DD) = 1 - N(DD) \tag{14}$$

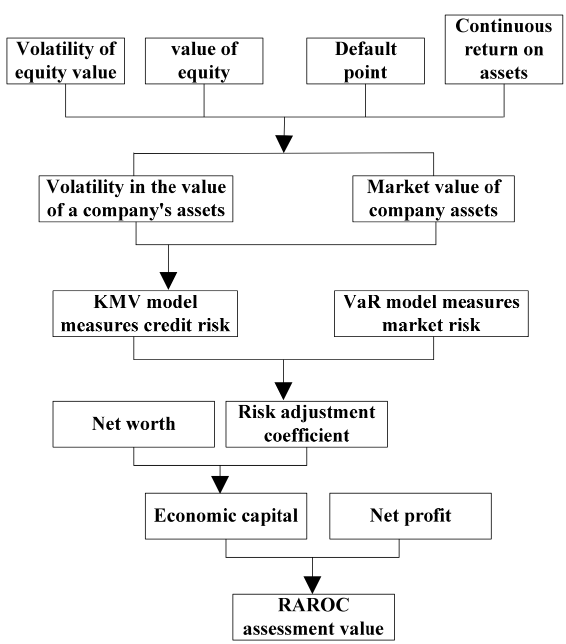
To sum up, the adjustment coefficient η of risk is expressed as follows:

$$\eta = EDF + R * T \tag{15}$$

RAROC can be obtained by substituting the coefficient into formula (5).

The basic procedure of RAROC business risk information value assessment is to calculate the risk adjustment coefficient based on KMV model and VaR model. The risk adjustment coefficient is used to adjust the risk of net assets reflected in the relevant statements to obtain the economic capital of the company. The results of RAROC value assessment are reflected through the statements, as shown in detail in Figure 7. As shown:

Figure 7 RAROC value assessments



3 Experiments and discussion

In order to verify the evaluation effect of RAROC-based business risk information value evaluation model, an experiment was conducted. Experimental data sources: The data of A-share listed companies from 2015 to 2018 are selected as research samples. The data selection criteria are as follows:

1. For the purpose of ensuring the comparability of time series analysis and the sustainability of company value evaluation, companies issuing A shares from January 1, 2015 to December 31, 2018 are selected.
2. Requirements have not experienced major restructuring.
3. Considering the particularity of RAROC operation in business comprehensively, the financial industry should be excluded.

After the above criteria, 1,015 listed companies are selected. The data are from the windows database and the annual reports of listed companies. The model is implemented in MATLAB.

In order to better verify the accuracy of the evaluation results, the following indicators were used to test the model:

1. fitting goodness index GFI
2. standard fitting index NFI
3. comparing fitting index CFI
4. approximate root mean square error RMSEA.

The accuracy of evaluation of different research results is as follows:

Figure 8 Accuracy comparisons of different research findings, (a) comparison of GFI of different research results (b) NFI comparison of different research results (c) CFI comparison of different research results (d) RMSEA comparison of different research results

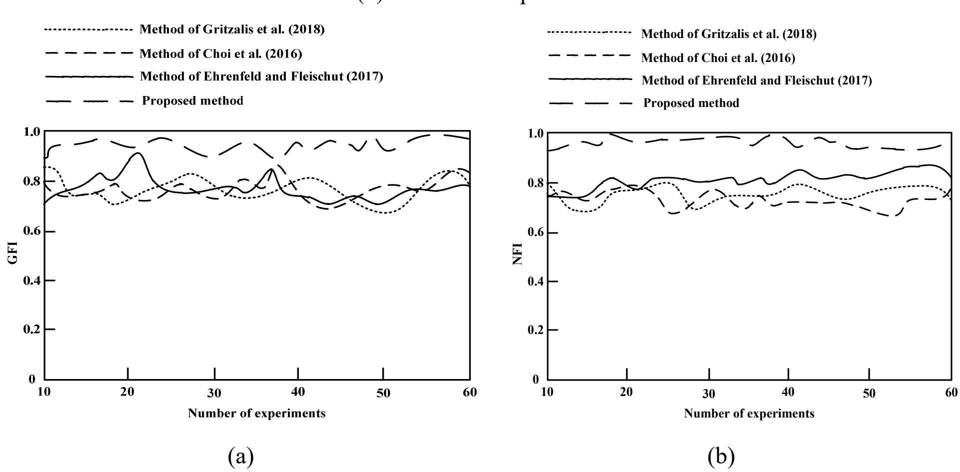
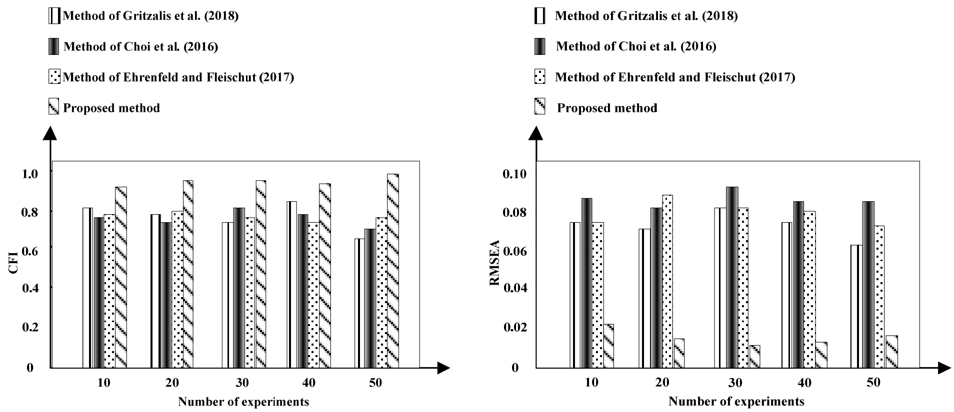


Figure 8 Accuracy comparisons of different research findings, (a) comparison of GFI of different research results (b) NFI comparison of different research results (c) CFI comparison of different research results (d) RMSEA comparison of different research results (continued)



(c) (d)

From Figure 8, it can be seen that the values of goodness of fit index, standard fitting index and comparative fitting index are all between 0.9 and 1.0, while the values of other methods are lower than 0.9. The higher the exponential value, the better the fitting effect of the method, which proves that the application effect of this method is better; the approximate root mean square error value of this method is better. The lower the approximate root mean square error value is, the higher the accuracy of the method is. It can be proved that the method in this paper has better accuracy and higher accuracy than other methods in the range of 0.06–0.09. In order to get more accurate evaluation results, the model cleans the data on the basis of data collection, and transforms the basic data after processing into commercial value, which elementarily improves the accuracy of evaluation. When RAROC is used for evaluation, the accuracy of evaluation is further improved by taking into account both benefits and risks.

4 Conclusions

1 The comprehensive performance of risk management is an important part of the comprehensive competitiveness of enterprises, and it is also a representative of diversity and complexity. It is very important to evaluate the comprehensive performance of risk management for the development of the industry.

2 In view of the poor accuracy of the current business risk assessment methods, this paper proposes a RAROC-based business risk information value assessment model.

3 Using the crawler search method with topic search to collect business information data, introducing extended tree structure to realise data cleaning, evaluating the value of business risk information through RAROC, calculating the risk adjustment coefficient by VaR model and KMV model, thereby adjusting the risk of net assets reflected in relevant reports. The report forms are used to reflect the results of RAROC valuation.

4 The experimental results show that the goodness-of-fit index of the proposed model is close to the standard fitting index and the fitting index, and the approximate root mean square error is less than 0.02, which has high accuracy and robustness.

5 In the process of RAROC operation, the capital market information must be sufficient. Therefore, the next step is to focus on the analysis of the adequacy of market information data in order to further improve the accuracy of evaluation.

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