The Research and Application of Enterprises' Dynamic Risk Monitoring and Assessment Model Based on Related Time Series

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***Abstract*—For the risk management problem of key enterprises in the area, we propose a time-series based risk monitoring and assessment model which could manage and predict enterprises' dynamic risk levels. Our model takes a systematic method to monitor and evaluate enterprises' various types of risk indicators: by collecting real-time categorical data through pre-designed data-collection portal, the model applies Z-score algorithm on processing and normalizing enterprises' categorical data and generates a time-series based risk intensity matrix. After that, our model uses entropy method to assign different weights on risk indicators to generate initial comprehensive risk index values; by applying the superposition of time-series risk attenuation function on the initial risk index values, we get the overall risk index values which is used to reflect enterprises' business risks. The simulation results of our method prove that our risk management model provides an effective solution to monitoring and evaluating enterprises' risks in the region. We have built monitoring and assessment information systems for several enterprises based on this risk management model; the purpose of this paper is to explain procedures the model takes to implement risk monitoring and assessment functions.**

***Index Terms*—Risk sequences, Z-score, Index attenuation function, Entropy**

I. Introduction

During the financial crisis period, the existence of mutual-chain protection problems among enterprises may cause regional risk chain reaction: one enterprise with serious business risks will always affect several related enterprises in the chain which will cause multiplied economic losses. In this background, related government departments try to help these affected enterprises solve risk problems to maintain social stability and at the same time, positively seeking solutions to monitoring and controlling enterprises' risks in a precautious manner.

From previous literature reviews about risk monitoring and assessment models, we find current researches of enterprises' risk management models mainly focus on designing risk monitoring models to prevent enterprises' bankruptcy and methods to improve governments' external supervision [1] [2]. These researches basically just study enterprises' cross-section business data for static risk analyses; however, enterprises' risks are always dynamic in nature which change with time constantly, static analyses are not accurate enough to reflect the time-series characteristic of those risk indicators that enterprises care about.

Our paper, from the perspective of government departments' supervision, presents a related time-series based [3] dynamic monitoring and assessment model to analyze enterprises' business risk intensity levels. The steps that we take to implement this model include collecting and standardizing enterprises' business data, building a time-series based matrix with observed risk indicators, using Z-score [4] method to normalize risk indicators as well as conducting intense assessment on individual risk indicator; choosing entropy values and weights for different risk indicators based on previous business data, and then applying time-series attenuation function on the initial risk index values. Finally we will get comprehensive risk index values which could be used to reflect enterprises' overall and regional risk levels in a certain period. Our model imports several concepts including time-series risk matrix, risk indicators and index values, as well as the superposition of related time-series attenuation function which in total make our model an effective method to predict enterprises' business risk intensity levels.

II. Monitoring and Assessment Model Design

A. Data Standardization and Normalization Model

Enterprises' business data involve various categorical data which includes main business income and changing information, power consumption, water and gas usage; asset, dropdown and financing ratios; back pay, debit interests, arrearage and job cut rates; the number of enterprises in mutual-chain protection and illegal business behaviors, etc. Our data comes from a dozen business management departments of related governments and enterprises. And these business data are filtered to become different risk indicators for our enterprises' monitoring and assessment model. The process of data conversion and calculation will be explained in the following steps:

Step 1: Create a time-series based matrix $D_{it}(n \times T)$ at time t.
After collecting enterprises' actual business data within one-month period, enterprises' business data would be converted and standardized to meet the calculation prerequisites of our model. For example, if there are n different categorical business data items being collected within one month, in a continuous period t $(t = 1, 2, \cdots, T)$, values of a particular collected item i (i $\in$ n) will constitute the time-series sequence of this data item during period t. We use the vector model to present time-series sequence of single business data item during a continuous period of t which is described in the following formula:

$$D_t = \{d_{i1}, d_{i2}, \cdots, d_{iT}\} \tag{1}$$

Different categorical business data items constitute the time-series matrix for our sample business data and that we use the matrix model in formula (2) to present such kind of time-series matrix.

$$D_{it} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1T} \\ d_{21} & d_{22} & \cdots & d_{2T} \\ \vdots & \vdots & \vdots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nT} \end{bmatrix} \tag{2}$$

Step 2: Use Z-score to normalize collected data.
In formula (2), there could be two kinds of observed values for the data item d_{it}: arithmetic and logical values which usually correspond to different units and reflect distinctive risk intensity values. Besides, arithmetic and logical values of d_{it} usually have different dimensions and order of magnitude, thus the value of each d_{it} data needs to be preprocessed to fit our model calculation requirements.
For d_{it} with arithmetic values, the model uses Z-score standardization method to process their values, the conversion function is described as:

$$X_{it} = \left(d_{it} - \bar{d_{it}}\right) / \rho_{it} \tag{3}$$

In formula (3),
$\bar{d_{it}} = \frac{1}{T} \sum_{t=1}^{T} d_{it}$; $\rho_{it} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left(d_{it} - \bar{d_{it}}\right)^2}$

For d_{it} with logical values, we use one-bit constant value (0, 1) to present d_{it} data.

Step 3: Create a standardized time-series based risk-index-value matrix $X_{it}(n \times T)$ at time t. After step 2, all the collected d_{it} values have been standardized and normalized; and the values are used to create time-series based multiple-risk-indicators matrix which is presented in formula (4):

$$X_{it} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1T} \\ x_{21} & x_{22} & \cdots & x_{2T} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nT} \end{bmatrix} \tag{4}$$

B. *Single Risk Indicator Assessment Model*

Single risk indicator evaluation model is used to measure risk levels when enterprises are faced with a single source risk. Single risk model uses risk-indicator classification method to assess risk levels of single source risk; the model uses risk degree variable $y_i(t)$ to describe individual risk indicator's risk levels, and the function to calculate the value of $y_i(t)$ in certain period of time is represented by $y_i(t) = f(x_i(t))$.
The value of single arithmetic risk indicator after being standardized by Z-score method, is fluctuating around value 0: if the risk indicator value is above 0, the risk level is above the average risk level; if indicator value is below 0, then the risk level is below the average. The standard deviation of individual risk indicator's Z-score is used to describe individual risk indicator's intensity levels.

According to the actual business data we collected, single risk indicator's levels are classified into four levels, degree 1-4, with level 1 the least risk level and level 4 the highest. During the data processing period, risk indicators are transferred to contrary index values and the model will use formula (5) to present risk levels of individual risk indicator.

$$y_i(t) = \begin{cases} 1, & x_i(t) \in (-\infty, 1] \\ 2, & x_i(t) \in (1, 1.5] \\ 3, & x_i(t) \in (1.5, 2] \\ 4, & x_i(t) \in (2, \infty) \end{cases} \tag{5}$$

For individual logical risk indicator, the model uses one-bit constant value (0, 1) to process risk data; thus the risk level of a single logical risk indicator is classified into only two levels, 1 and 4.
After evaluating individual risk indicator's levels in a period, the matrix in formula (4) will become the time-series based risk intensity level matrix for all risk indicators, presented in formula (6):

$$Y(t) = \begin{bmatrix} y_1(1) & y_1(2) & \cdots & y_1(T) \\ y_2(1) & y_2(2) & \cdots & y_2(T) \\ \vdots & \vdots & \vdots & \vdots \\ y_n(1) & y_n(2) & \cdots & y_n(T) \end{bmatrix} \tag{6}$$

C. *Comprehensive Assessment Model*

Comprehensive risk assessment model is used to assess enterprises' overall risk intensity levels when there are multiple risk indicators. Based on the risk monitoring and assessment model of individual indicator and their risk intensity levels, the model creates a comprehensive risk assessment model to calculate enterprises' overall risk intensity index values. According to enterprises' overall risk intensity values, our model will generate five-leveled risk assessments and 3-leveled risk alerts correspondingly.
The model will conduct Weighted operations on enterprises' individual risk indicator through entropy method. Traditional entropy method merely considers cross-section data when determining entropy values, but for time-series data, choosing entropy values through analog method would be more proper

in our case. We will use the history business data of those enterprises in danger (enterprises which have gone bankrupt or are in high business management risks) provided by governments departments to determine the entropy value for risk intensity's index values. The steps to get entropy value are described as follows:

Step 1: Determine the Information Entropy for Risk Indicators.

Suppose there are m enterprises in danger, for particular enterprise in danger j (j = 1, 2, ..m), the information entropy of a risk indicator i is:

$$E_i = \frac{-1}{\ln m}\sum_{j=1}^{m} p_{ij}\cdot \ln p_{ij}, \quad p_{ij} = X_{ij} / \sum_{j=1}^{m} X_{ij} \tag{7}$$

X_{ij} is the normalized value of the ith observed risk indicator of the jth enterprise in danger.

Step 2: Determine the Weights for Different Risk Indicators.

$$w_i = (1 - E_i) / \sum_{i=1}^{n}(1 - E_i) \tag{8}$$

After weights of each indicator are determined, the model will calculate jth enterprises' comprehensive risk index values by weighted average algorithm, which is expressed by in formula (9):

$$R_j(t) = \frac{1}{L}\sum_{i=1}^{n} y_{ij}(t)\cdot w_i \tag{9}$$

The $y_{ij}(t)$ in Formula (9) is the ith risk indicator value generated by single assessment model of jth enterprise in period t. L = 4 is the sum of single risk indicator level as described in formula (4). So far the values of comprehensive risk level have been normalized. Enterprises' risks will be divided into five levels, which are high, medium high, medium, low, minute risk levels with number 5 representing the highest risk level and 1 the lowest. The distribution of jth enterprises comprehensive risk intensity index is presented as Formula (10):

$$R_j(t) = \begin{cases} 5, & R_j(t) \in [0.85, 1.0] \\ 4, & R_j(t) \in [0.75, 0.85) \\ 3, & R_j(t) \in [0.65, 0.75) \\ 2, & R_j(t) \in [0.50, 0.65) \\ 1, & R_j(t) \in [0, 0.50) \end{cases} \tag{10}$$

The three-leveled risk alerts are presented by three different colors, red, orange and yellow which correspond to high, medium high and medium level enterprises' risks.

D. The Superposition of Historical Risk Data Model

In order to evaluate enterprises' risk index values more accurately, we need to consider the influence of enterprises' previous risk data's accumulation on current enterprises' risk intensity levels. We use time attenuation function to assess the influence of historical risk data superposition on current enterprises' comprehensive risk index values. We construct the historical-risk-indicators' time attenuation function based on the fact that the longer the risk point appeared in history, the less the influence would the accumulation of risk points on current risk intensity index be. The time attenuation function model is presented in Formula (11):

$$y^*{}_t = y_t + \alpha y_{t-1} + \alpha^2 y_{t-2} + \cdots + \alpha^{\beta-1} y_{t-(\beta-1)} \tag{11}$$

In the Formula (11) value $\alpha\,(0 \le \alpha \le 1)$ is the attenuation coefficient and value$\beta\,(\beta \ge 1)$ is the length variable which presents the time span of historical risk data that could potentially influence current enterprises' risk intensity levels. Usually we will only consider the latest three risk points which means $\beta = 4$ and at the same time picking up a proper α value will help generate better quantified historical risk prediction values. After the superposition of historical risk data, the time-series based risk intensity matrix in formula (6) has changed to the model in formula (12) showing risk levels added with continuity characteristic.

$$Y^*(t) = \begin{bmatrix} y^*{}_1(1) & y^*{}_1(2) & \cdots & y^*{}_1(T) \\ y^*{}_2(1) & y^*{}_2(2) & \cdots & y^*{}_2(T) \\ \vdots & \vdots & \vdots & \vdots \\ y^*{}_n(1) & y^*{}_n(2) & \cdots & y^*{}_n(T) \end{bmatrix} \tag{12}$$

So far we have got enterprises' overall risk intensity index values by using attenuation function with the superposition of historical risk data and indicates our model's inclusion of review-period historical data.

III. Simulation Results

A. Comprehensive Risk Assessment and Comparison Study

Based on the normalized time-series business data and by using our monitoring and assessment model, we make a comparative study of enterprises' risk intensity index trend and the results are depicted in graph 1: we make two risk intensity index lines with one applied with the superposition of historical risk data and the other does not which correspond to superposition risk index and normal risk index line distinctively.

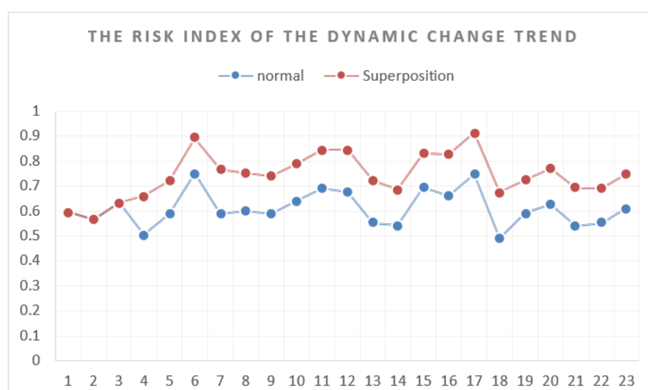

Fig. 1. Dynamic risk index change chart in 23 months for some enterprise

From figure 1, we can see that at the beginning of the fourth month, as our model starts to use historical risk data superposition to calculate enterprises overall risk index values, the two risk index lines begin to show different trends; with the value of superposition risk intensity index line higher than that of the normal risk index line.

From figure 1 we can see that the enterprise has high business risks at the 6th, 11th, 12th and 17th month with high risk index values of 0.8936075, 0.850076, 0.850515 and 0.91468 which generates level-5 risk alerts; the actual business management conditions of this enterprise, according to our actual investigations, reflect similar high business risks as our model suggests. Related government departments, which have correctly predicted risk levels of the enterprises through our supervision and evaluation model, could take efforts in time to investigate enterprises' actual risk conditions and help them solve problems. However, the normal risk index line, with no superposition model applied, shows risk index values of 0.7490315, 0.69, 0.678125 and 0.7495 which only indicate level-3 risk alerts. Level-3 medium risk alerts may not be serious enough to cause enterprises' and governments' attention.

From the above comparison study, we can tell that our monitoring and assessment model is reliable in predicting enterprises' business risks; the model with historical risk information superposition generates more accurate risk level alerts which is closer to enterprises' actual business conditions.

IV. Conclusions

This paper presents a time-series based dynamic model, which provides enterprises with dynamic business risk classification, alerts generation and notification updates. In this model, the transition from multiple risk indicators' intensity levels to comprehensive risk index values provides ground for enterprises' risk prediction. The simulation results of our later comparison studies of 171 enterprises' sample business data in total shows that our model, which reflects the influence of historical risk data's accumulation on current business risks, could predict enterprises' risk levels accurately with reduced error rate of 1.85% and improved correctness rate of 98.8 %. Compared with previous researches on enterprises' risk assessment and monitoring models, we summarize three distinctive characteristics our model has based on the overall model analyses and simulation results description:

(1) The risk index attenuation function could reflect the transformation from risk data's quantitative accumulations to qualitative leveled risk alerts generation, which provides an effective method to improve the retrospecting ability of some dynamic risk accumulation models.

(2) From our empirical studies, we know that time-series based risk-accumulated assessment model could reflect the dynamic changing characteristic of enterprises' risk supervision; and the model provides a scientific method for related government departments to substantiate potential enterprises' business risks.

(3) The monitoring and assessment model has certain universality, which could be used as references for further researches on the quantitative analysis of dynamic risks.

Acknowledgment

The authors would like to thank all the reviewers for their helpful suggestions to improve the paper.

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