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Organization bankruptcy risk forecasting methodology based on analytic hierarchy process

La metodología para predecir el riesgo de quiebra de las organizaciones basada en el método de análisis de jerarquías

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Abstract
In this article, the authors propose a methodology for assessing the bankruptcy risk of organizations operating in the framework of one industry. The authors identify six criteria - qualitative factors influencing the bankruptcy of an organization: industry risk (IR), management risk (MR), financial flexibility (FF), creditability (CR), competitiveness (CO) and operating risk (OR). The authors use the hierarchy analysis method to obtain a vector of aggregated default risk estimates.
key words: corporate bankruptcy, analytic hierarchy process, expert evaluation

Resumen
Los autores proponen una metodología para evaluar el inicio del riesgo de quiebra de las organizaciones que operan en el marco de una industria. La técnica conlleva pasos específicos e incluye cinco etapas. Se identifican seis criterios como factores que influyen en la quiebra: riesgo industrial (IR, industry risk), riesgo de gestión (MR, management risk), flexibilidad financiera (FF, financial flexibility), credibilidad (CR, creditability), competitividad (CO, competitiveness) y riesgo operativo (OR, operating risk). Se utiliza el método de análisis de jerarquía para obtener un vector de estimaciones de riesgo de incumplimiento agregadas.
Palabras clave: quiebra de una organización, método de análisis de jerarquía, evaluaciones de expertos

1. Introduction

Bankruptcy is a legal process that takes place when a company is unable to resolve its financial obligations. The financial assets of companies are sold to repay debts to creditors, which leads to huge losses for both owners and investors. Thus, it is necessary to develop effective bankruptcy forecasting strategies at an earlier stage in order to avoid a financial crisis. parties Interested in determining the financial sustainability of an organization can be not only owners and investors. Various individuals and legal entities need information about the "real

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state of affairs in the company they are associated with": from suppliers and partners to current and potential employees.

From an institutional point of view, the more information all economic agents possess the less will be the risk of transaction costs. In other words, due to the completeness of the information obtained as a result of applying a simple and reliable methodology, we can assess financial stability and minimize the risk of financial distress or even bankruptcy. Key market players will trust this organization more: customers will be confident in the quality of the products; employees - in salaries and higher bonuses; suppliers, contractors and partners - in the reliability and creditability of the organization as a borrower, which, in turn, will positively affect the business reputation of this company.

2. Basic methodological approaches

Today in the literature meets various approaches to bankruptcy prediction, a significant part of which relies on methods of statistical data analysis. Such methods allow identifying hidden patterns in the source data characterizing the financial stability of a company. One of the most popular approaches is based on the development of quantitative models to predict the likelihood of bankruptcy in a company. Fundamental in this class of models, which has become widespread, is the Altman Z Score model (Altman, 1968). This model belongs to the class of multiple discriminant analysis models and allows, on the basis of financial and accounting reporting indicators, to determine whether a company is headed for bankruptcy or not.

Later a number of scientists in numerous studies continued the development of quantitative models, generalizing the Altman model that has become classical, using a whole range of data analysis tools, ranging from factor analysis to neural networks - discriminant analysis (Today in the literature meets (1994), Chesser, 1974), logit models (Ohlson, 1980), probit models (Zmijewski, 1984), neural networks (Bredart, 2014, Fletcher, et al (1993), Odom, et al (1990), Tam, et al (1992), probabilistic methods (Jarrow, et al (1995), Merton, 1974). The core of this approach is training, according to certain rules, of classifying functions that separate classes of potential bankrupts from financially stable organizations. Note that for the successful implementation of these algorithms, it is necessary to have a significant database, including a feature description of objects of both classes. In reality it is seldom available, as the collection of such information requires additional time and financial costs.

Another approach is to automatically extract bankruptcy forecasting rules from financial knowledge bases - expert evaluations. Expert evaluations play an important role in the real process of predicting default risk and work with their individual subjective knowledge structure to develop relevant conclusions, while combining available quantitative and qualitative information that can be used to assess default risk (Messier, et al (1988); Myoung-Jong Kim, et al (2003), Martin, et al (2014), Shaw, et al (1990), Shin, et al (2002). At the same time interactive methods, such as interviews or questionnaires, can be applied to form an expert knowledge base related to bankruptcy forecasting. Optimization of such models is most often based on genetic algorithms. The advantages of this method are the breadth of coverage, high portability and reliability of calculations. The key flaw in short comes down to implementation speed and parameter settings. Due to the rapid development of computer technology, parallelization technologies and a significant number of studies in this area, these problems are partially solved. At the same time in modern Russia it will require additional financial injections related to the purchase of software, computer equipment, as well as the hiring employees of certain qualifications. This is rarely affordable for small businesses.

Finally let us note a group of methods based on fuzzy inference systems. They are designed to convert the values of an input variable based on the use of fuzzy production rules. These rules are implemented in the form of premises or conditions presented in the form of fuzzy linguistic utterances. If one is to assess bankruptcy risk of a company, one is to formulate a complete, consistent system of logical rules consisting of certain criteria

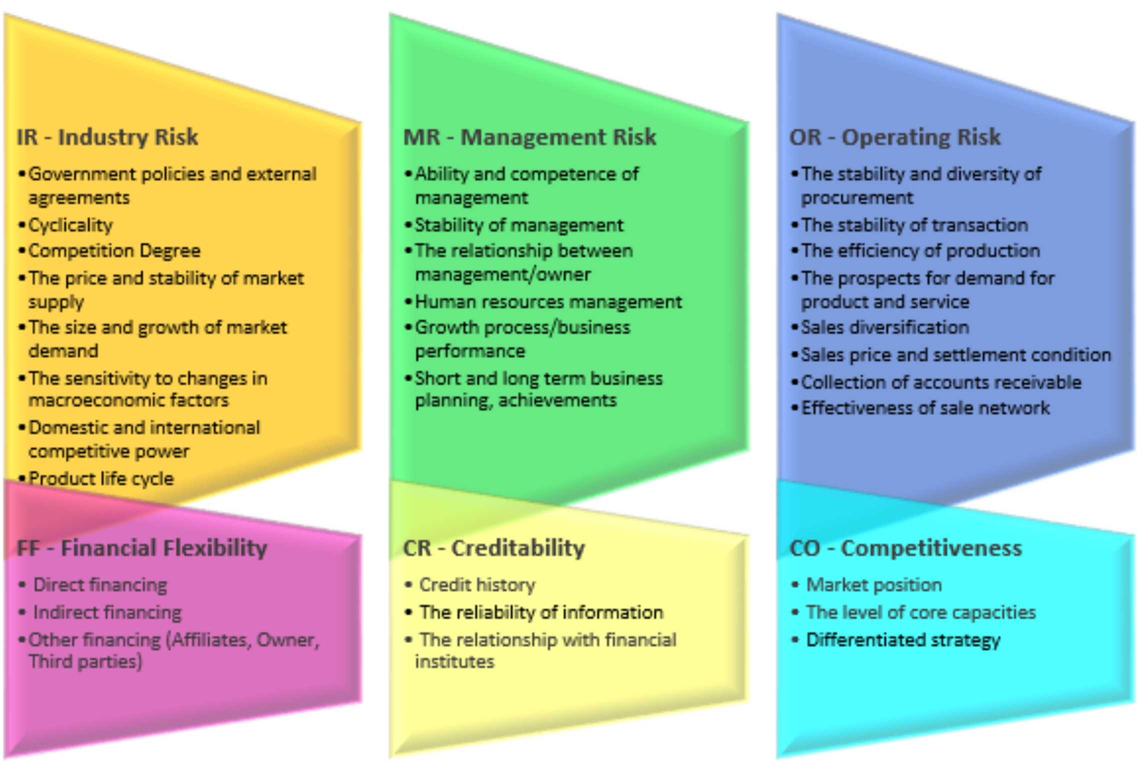
(Arinichev, et al (2016), Rainarli, et al (2015), Shnaider, et al (1989), Tudela, et al (2005). The advantages of the method include the ability to teach a decision-making system "without a teacher". However the set of rules is formed on the basis of expert opinions and is subjective.

3. Methodology

In this paper we consider the organizations' bankruptcy risk forecasting methodology based on the concept of the analytic hierarchy process (AHP). The purpose of this approach is to determine the ranked series for many enterprises of a certain industry, taking into account the priority of risks.

We follow the classification given in the scientific studies (Martin, et al (2014), Myoung-Jong Kim, et al (2003), and identify six criteria - qualitative factors influencing the bankruptcy of an organization: industry risk (IR), management risk (MR), financial flexibility (FF), creditability (CR), competitiveness (CO) and operating risk (OR) (Fig. 1). IR reflects industry stability and growth, and competition degree and characterizes the probability of losses due to changes in the economic environment; MR is associated with management efficiency, depends on the competencies of a company's managers including top management, as well as the structural stability of a company, capability-based business plans; FF is understood as the ability of an enterprise to quickly generate the necessary amount of borrowed investment resources with the unexpected appearance of highly effective investment offers that provide new opportunities to accelerate economic growth; CR characterizes the reputation of the company associated with credit history, the accuracy of the information provided by the organization and relations with financial institutions; CO expresses the degree of competitive advantage determined by the market position and the capacity of available technologies; OR is the risk associated with the company performing business functions (procurement, production, sales, receivables collection policy), including the risks of fraud and some external events.

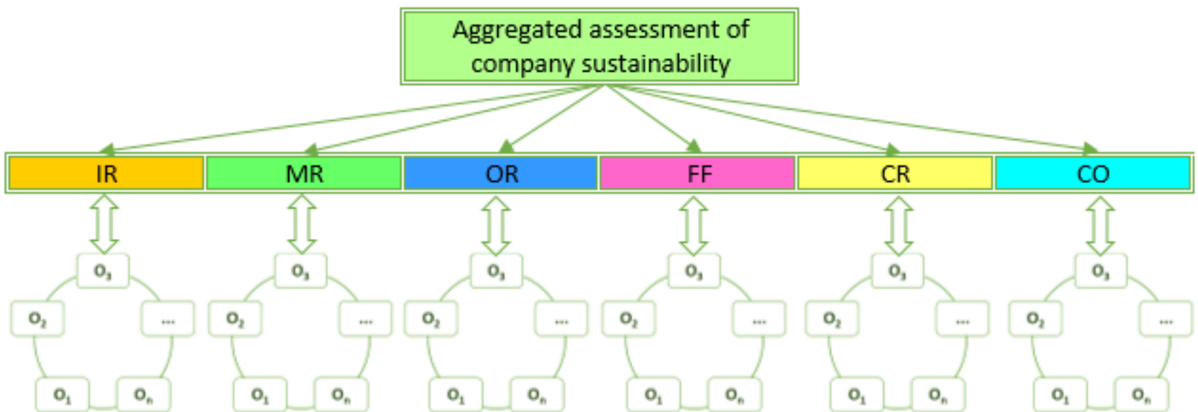
Figure 1
Types and risk factors (hierarchy criteria)



Source: own elaboration

The objects of choice and evaluation - alternatives - are business entities within a certain industry - enterprises. In this study, O_i represents these alternatives, while *n* corresponds to their number. Each of the alternatives will be evaluated in pairs with all the objects considered in this series from the point of view of prevailing over them for each criterion. In this case, the aggregated hierarchical structure of the task will look as follows (Fig. 2):

Figure 2
Aggregated hierarchical structure



Source: own elaboration

The methodology for assessing the occurrence of a default situation in this case involves the sequential implementation of the following steps (Silinskaya, et al (2017).

Stage 1. Assessment of the priority of the criteria

This assessment may depend on the purpose of obtaining an aggregate estimation of the sustainability of alternatives, industry, geographic and climatic dependence of the enterprises being assessed, its being part of special economic zones, regional characteristics, the availability of state support, as well as the attitude to the selected risks of the decision maker (DM) / expert. It is necessary to build and fill in the matrix of pairwise comparisons of criteria according to the rule (Table 1):

$$k_{ij} = \frac{k}{k_j},\ k_{ji} = \frac{1}{k_{ij}},\ k_{ii} = 1,\ i = 1,\ldots,6.$$

Table 1
Matrix of pairwise comparisons of criteria

		IR	MR	OR	FF	CR	CO
	№	***1***	***2***	***3***	***4***	***5***	***6***
IR	*1*	1	k_{12}	k_{13}	k_{14}	k_{15}	k_{16}
MR	*2*	k_{21}	1	k_{23}	k_{24}	k_{25}	k_{26}
OR	*3*	k_{31}	k_{32}	1	k_{34}	k_{35}	k_{36}
FF	*4*	k_{41}	k_{42}	k_{43}	1	k_{45}	k_{46}
CR	*5*	k_{51}	k_{52}	k_{53}	k_{54}	1	k_{56}
CO	*6*	k_{61}	k_{62}	k_{63}	k_{64}	k_{65}	1

Source: own elaboration

It should be noted that k_i, k_j are expert evaluations of risk elements, which ultimately enter the aggregate estimation of the sustainability of alternative enterprises. These estimates reflect the degree of importance of one type of risk over another. They can be determined by experts both on their own scale and using a scale of relative importance (Petrichenko, et al (2016). In addition, $k_{ij}>1$ if the *i*-th criterion prevails over the *j*-th criterion, and $k_{ij}<1$ if otherwise.

Next, for each row we calculate the geometric mean criterion score and normalize it. Thus, we obtain the weighting coefficients of the criteria which determine them in a ranked series in terms of importance.

Stage 2. Assessment of the consistency of judgments

At each stage, when constructing matrices of pairwise comparisons, it is necessary to additionally control the consistency of expert judgments when comparing the elements of these matrices. To do this, we calculate the maximum eigenvalue of the matrix k_{max} by the component-wise product of the elements of each row of the matrix of pairwise comparisons by the normalized vector of weight coefficients (priorities) determined for it and the further sum of the obtained products. The measure of consistency of relative estimates is calculated using the consistency index according to the formula:

$$IC = \frac{k_{\max} - n}{n - 1},$$

where *n* is the number of comparison elements at this stage (for criteria it is 6).

Then we adjust the obtained indicator to the value of random consistency corresponding to the order of the constructed matrix of pairwise comparisons. So we determine the final *RC* consistency relation, which should be included in the interval [0; 0,1], otherwise the judgments in the matrix of paired comparisons must be reviewed to ensure that *RC* matches the recommended interval.

Stage 3. Ranking of alternatives by criteria (risks). Getting local priorities

For each criterion we build a matrix of paired comparisons of alternative objects. When comparing them from the point of view of risks, the predominance of one object over another must be evaluated in the opposite sense: the less the alternative is exposed to a certain risk compared to another, the higher its prevalence over it, the greater the relative rating in the corresponding cell of the matrix of pairwise comparisons. In this case, one can also use the selected quantitative indicators characterizing the degree of exposure of the alternative to the risk. Then, to obtain a relative assessment of the comparison of alternatives, it is enough to calculate the ratio of the values of these indicators for different alternatives. At the same time, moving along the row, it is necessary to fix the numerator or denominator of relations, depending on the meaning of the chosen indicator. If its meaning in the assessment is defined as “the more, the better”, then the numerator is fixed, if “the less is better”, then the denominator of these fractions becomes constant in the calculation of relations.

In the case when the estimates of the comparison of alternatives are determined by the ratios of the values of the indicators, the consistency of all judgments in the matrices of pairwise comparisons is 100%, and then these matrices no longer require additional verification and adjustment.

The matrix of pairwise comparisons of alternative objects will have the following form (Table 2):

Table 2
Matrix of pairwise comparisons of alternatives, vector of local priorities

Criterion		O_1	O_2	O_3	…	O_n	Geometric mean	Local Priority Vector
	№	*1*	*2*	*3*	…	*n*		
O_1	*1*	1	q_{12}	q_{13}	…	q_{1n}	$q_1 = \sqrt[n]{\prod_{j=1}^{n} q_{1j}}$	$\delta_1 = \frac{q_1}{q}$
O_2	*2*	q_{21}	1	q_{23}	…	q_{2n}	$q_2 = \sqrt[n]{\prod_{j=1}^{n} q_{2j}}$	$\delta_2 = \frac{q_2}{q}$
O_3	*3*	q_{31}	q_{32}	1	…	q_{3n}	$q_3 = \sqrt[n]{\prod_{j=1}^{n} q_{3j}}$	$\delta_3 = \frac{q_3}{q}$
…	…	…	…	…	…	…	…	…
O_n	*n*	q_{n1}	q_{n2}	q_{n3}	…	1	$q_n = \sqrt[n]{\prod_{j=1}^{n} q_{nj}}$	$\delta_n = \frac{q_n}{q}$
Total							$q = \sum_{l=1}^{n} q_l$	1

Source: own elaboration

We build six matrices of this type to evaluate alternatives for all risk criteria. The necessary consistency check is carried out in accordance with the algorithm described in the second stage

***Stage 4*. Calculation of aggregated (global) estimates of alternatives**

Since, from the point of view of each criterion, the alternatives are arranged in different ranked rows of local priorities, we need to “add” them to general (aggregated) estimates. In this case, it is necessary to take into account the significance of each of the criteria determined at the first stage of the application of HAM.

We need to calculate the scalar product of the criteria priority vector (the result of the first stage) and the component vector of the estimates of each alternative object (third stage) in order to obtain aggregate estimates of the alternatives. Thus, we obtain the *n* component of the global priority vector (Table 3).

Let K1, ..., K6 be the components of the criteria (risk) priority vector obtained on the basis of Table 1; δ_{ij} are components of local priority vectors for the *i*-th alternative according to all criteria; *j* is the number of the criterion, *i* = 1, …, *n*, *j* = 1, …, 6. Thus, all estimates of a particular alternative, formed from the point of view of each criterion, will be located along the rows of the final matrix.

Table 3
Calculation of aggregate estimates of the sustainability of alternative enterprises

A Number of Alternatives	Criteria						Aggregate Estimates Vector
	IR	MR	OR	FF	CR	CO	
	K_1	K_2	K_3	K_4	K_5	K_6	
O_1	δ_{11}	δ_{12}	δ_{13}	δ_{14}	δ_{15}	δ_{16}	$\omega_1 = \sum_{j=1}^{6} K_j \cdot \delta_{1j}$
O_2	δ_{21}	δ_{22}	δ_{23}	δ_{24}	δ_{25}	δ_{26}	$\omega_2 = \sum_{j=1}^{6} K_j \cdot \delta_{2j}$
O_3	δ_{31}	δ_{32}	δ_{33}	δ_{34}	δ_{35}	δ_{36}	$\omega_3 = \sum_{j=1}^{6} K_j \cdot \delta_{3j}$
…	…	…	…	…	…	…	…
O_n	δ_{n1}	δ_{n2}	δ_{n3}	δ_{n4}	δ_{n5}	δ_{n6}	$\omega_n = \sum_{j=1}^{6} K_j \cdot \delta_{nj}$
Sum of Estimates							$\sum_{i=1}^{n} \omega_i = 1$

Source: own elaboration

In the last column of the table, the final assessments of alternative objects are determined from the position of all comparison criteria, as well as taking into account their importance to the decision maker.

Based on the results of the ranking of enterprises, we can obtain their classification by determining for each class the interval of permissible values of the obtained ranks.

4. Conclusions

In this study, the authors propose an approach based on the method of hierarchy analysis. It allows us to rank enterprises of one industry by the degree of increase / decrease in the risk of default of each of them. The methodology is a multi-step procedure and involves the use of expert evaluations, which are collected with the aim of forming pairwise priorities of the criteria. To concretize the study, the authors selected six such criteria for the onset of bankruptcy risk. In accordance with the obtained matrix of paired comparisons of criteria, the analytic hierarchy process generates the weight of each of them, after which for each fixed criterion the method assigns an individual rating to each organization. Based on the final convolutions, we obtain a vector of aggregated estimates in the ordinal scale, which after normalization can be interpreted as the probabilities of classifying each individual organization as a bankruptcy class. The threshold for separating one class from another is selected individually by each organization, but most often it is assumed to be equal to 0.5 (> 0.5 - bankrupt, <0.5 – non-bankrupt).

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