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SELECTION OF VARIABLES IN THE FUNCTION OF IMPROVING THE BANKRUPTCY PREDICTION MODEL

Abstract

The significance of early disclosure of the probability of launching a bankruptcy proceeding leads the authors to develop a model of high prediction power. In this way, the authors use different variables and statistical tools, and techniques. The impact of the economic environment and data availability limits the introduction of certain variables in bankruptcy prediction models. The paper aims to explore attitudes in existing literature regarding the selection of variables used to develop models for predicting bankruptcy, their characteristics, limitations, and impact on the power of predictions. The labor findings show that the historical character of the data and the conservative approach to financial reporting have turned authors to the use of non-financial and market variables. For the most part, efficient markets absorb all external and internal information and future predictions, which are read through market prices. However, this assumption does not apply to less developed markets, and the use of market variables is questionable. In conditions of increased systemic risk, macroeconomic variables can be good indicators for predicting the likelihood of bankruptcy. Developing a model for predicting bankruptcy requires looking at the economic environment and choosing variables that correspond to existing business conditions. With the changing economic environment, adjustment of the model needs to be made so that the accuracy of the forecast does not decrease.

Key words: *financial variables, non-financial variables, market variables, statistical variables, bankruptcy forecasting model.*

JEL classification: *G33*

ИЗБОР ВАРИЈАБЛИ У ФУНКЦИЈИ УНАПРЕЂЕЊА МОДЕЛА ЗА ПРЕДВИЂАЊЕ СТЕЧАЈА

Апстракт

Значај раног откривања вероватноће покретања стечајног поступка предузећа наводи ауторе на развијање модела високе моћи предвиђања. При томе, аутори користе различите варијабле и статистичке алате и технике.

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Утицај привредног амбијента и доступност података ограничава увођење одређених варијабли у моделе за предвиђање стечаја. Рад има за циљ да истражи ставове у постојећој литератури у вези селекције варијабли које се користе за развијање модела за предвиђање стечаја, њихових карактеристика, ограничења и утицаја на моћ предвиђања. Налази рада показују да су историјски карактер података и конзервативни приступ у финансијском извештавању окренули ауторе на употребу нефинансијских и тржишних варијабли. Највећим делом, ефикасна тржишта апсорбују све екстерне и интерне информације и будућа предвиђања, што се очитава кроз тржишне цене. Међутим, за мање развијена тржишта, ова претпоставка не важи, те је и употреба тржишних варијабли упитна. У условима повећаног системског ризика макроекономске варијабле могу бити добри индикатори за предвиђање вероватноће покретања стечаја. Развијање модела за предвиђање стечаја захтева сагледавање привредног амбијента и бирање варијабли које одговарају постојећим условима пословања. Са променом привредног амбијента потребно је извршити и кориговање модела како се прецизност предвиђања не би смањила.

Кључне речи: *финансијске варијабле, нефинансијске варијабле, тржишне варијабле, статистичке варијабле, модел за предвиђање стечаја*

Introduction

When developing a bankruptcy prediction model, the most crucial issue is choosing variables that will predict the likelihood of bankruptcy proceedings with the utmost accuracy. A large number of authors use variables that have been used in previous studies. According to the du Jardin survey (2009), 40% of the studies analyzed use variables used in earlier research.

How certain variables can be important for predicting bankruptcy in a country, with a change in the business environment and the impact of the same variable can vary. Therefore, some authors choose to explain more variables and use specific statistical techniques to obtain the optimal number of variables that define the likelihood of going bankrupt.

Most studies use account schedule indicators that describe a company's operations using data from financial statements. Nevertheless, to increase the model's predictive power, authors also introduce statistical, non-financial or market variables in addition to financial coefficients. Given the economic environment and availability of data, the use of certain variables can be limiting.

The paper aims to explore existing attitudes in the literature regarding the selection and application of different types of variables, their characteristics, usage limitations, and their impact on the accuracy of bankruptcy predictions in different economic environments.

The paper uses an analysis method, a descriptive analysis that describes the characteristics of individual types of variables and how they are collected, concerning the most commonly used variables in bankruptcy prediction models. On the other hand, the detailed analysis seeks to explain the use-value and limitations of individual variables through the views of authors derived from empirical research conducted in markets of varying degrees of development and different time frames. The paper covers studies from 1973 to 2010. The comparative analysis highlights the authors' similar and other views and conclusions regarding the pros and constraints and the recommendation of using certain variables to predict bankruptcy.

The paper is structured as follows: In the first part of the paper (now these numbers depend on whether you number the introduction, so correct it if necessary) are presented with financial analysis indicators, and data read from financial statements used to develop a model for predicting bankruptcy. The second part of the paper highlights the karate of non-financial variables. Then, the third part of the paper describes market variables with comparative power to predict models that use accounting and market data. The fourth part of the paper explains the use of statistical variables, with a view to the most commonly used. The conclusion summed up the survey results with main contributions and limitations of paper and the direction of future research.

Use of financial analysis indicators and financial statements to develop models for forecasting company bankruptcy

Financial indicators based on data from financial statements are the basis of models that analyze the business creditworthiness of the company, predict future business and the risk of bankruptcy. In addition to financial ratios, financial variables can be used to develop a model for predicting bankruptcy, including data from financial statements that can be used independently, such as the number of cash flows, sales revenues, the value of business assets, etc. However, the use of financial ratios in bankruptcy prediction models is much more common.

Financial ratios can analyze a company's business and track its movements over time as an efficient tool for summarizing large amounts of data. With the help of financial ratios, it is possible to compare the strengths and weaknesses of companies within the same business activity by quantifying specific aspects of the business. On the other hand, financial ratios are not comparable between companies of different industries, as they face other risks, capital requirements, and competition (Gill, 1994).

There are many financial ratios that can be calculated using data from financial statements, but only a specific, smaller set of ratios affects the prediction of company bankruptcy. Based on the characteristics that describe companies, financial ratios can be classified into several commonly used groups (Brealey, Myers & Marcus, 2001, p. 134-144):

- Debt ratio. Companies can be financed by borrowing from creditors. On that occasion, they undertake to pay part of the principal and the corresponding interest within the agreed terms. Debt is used for investment and, together with its own sources of financing, increases returns to shareholders in good business conditions. Also, in poor business conditions, the debt reduces the return to shareholders, bearing in mind that even then the company's obligation to repay the debt does not end. Debt ratios show how much debt an enterprise can take by comparing long-term debt with equity or long-term tied sources of financing, total liabilities with operating assets, or the ratio of profit before interest and taxes to interest expense.
- Liquidity ratio. An important segment of the analysis is the assessment of the company's solvency and fulfillment of due obligations. For that purpose,

the liquid assets that the company has at its disposal are considered, which can be easily transformed into cash. Compared to fixed assets, whose book value often does not correspond to the market value, with the most liquid form of working capital, it is easy to establish cash value on current accounts. However, the problem in liquidity analysis may arise due to the nature of working capital. Namely, working capital changes its shape quickly and easily, and liquidity ratios calculated based on financial statements are often outdated. In addition, companies can settle stocks before the end of the year, which will increase the company's liquidity and point out wrong conclusions. On the other hand, an increase in trade receivables or inventories without an increase in sales revenue may indicate inefficient management of these accounts, leading to future write-offs and losses rather than improved liquidity. It is therefore suggested that the liquidity ratio should be analyzed together with the efficiency ratios. The most commonly used liquidity analysis is the current, rigorous and cash liquidity ratio and the ratio of net current assets and operating assets. However, Mills and Yamamura (1998) argue that cash flow information may be more reliable for determining liquidity due to the historical nature of balance sheet positions.

- Efficiency ratio. Efficiency analysis is conducted in order to obtain information on how efficiently the company uses its resources. The following ratios are most often analyzed depending on the form of assets: asset turnover ratio (sales revenue / average operating assets) and inventory turnover ratio (costs of sold products / average value of inventories).
- Profitability ratio. The focus of observing profitability is the profit that the company makes. The analysis of the profit margin examines the share of sales revenue in net profit. If the company is financed partly from debt, then the profit is distributed to the company owners and creditors. In this case, the profit margin is calculated by comparing the sum of net profit and interest expenses with sales revenue. A significant indicator of profitability is the rate of return on operating assets, which is calculated by comparing net profit (or net profit increased with interest expenses) and average operating assets. Suppose the ratio of net profit and average value of capital is taken into account. In that case, the rate of return on capital is obtained, which shows how much profit the company generates on the engaged equity (Tomašević, Jović, & Vlaović Begović, 2019, p. 296).

Financial ratios are easy to apply, they do not require special skills for their calculation. However, the quality of the financial results obtained depends on the quality of the financial statements. Internal and external users should receive high-quality information on the company's operations based on financial reports, through financial ratios. Although there are different definitions of quality, international bodies and standard-setting committees consider that the quality of accounting information implies the reliability and transparency of data in financial statements (Camacho-Minano, & Campa, 2014, p. 77). Even assuming that the financial statements reflect an accurate and fair presentation of the company's operations, these are data relating to past events, "without appropriate guidance for future action, which may represent an improvement or deterioration in performance" (Prošić, 2014, p. 177).

These shortcomings of financial statements warn that business decisions should not be made solely based on analysis using financial statements, without the use of additional information. Decision-makers need information that they do not find in the financial statements concerning its performance and forecasting future business. For this reason, a new, integrated approach is emerging that combines financial and non-financial data for the purpose of evaluating the company's operations (Krstić, & Bonić, 2013).

Non-financial variables for developing a bankruptcy prediction model

There are a large number of non-financial variables that can be monitored and observed. The correct choice of non-financial variables is crucial for making business decisions, namely the variables that accompany the implementation and success of the strategy. Managers often rely on their perception when using non-financial variables without applying statistical and mathematical methods to confirm their assumptions (Krstić, & Sekulić, 2007, p. 78), which may indicate erroneous conclusions of the analysis.

One of the ways to collect non-financial information is the collection through integrated reporting, which includes financial and non-financial information about the company's operations, which raises the quality of corporate reporting. By flexibly adapting to the needs and requirements of stakeholders, the traditional financial and economic approach is expanded and improved (Bogićević, Domanović & Krstić, 2016, p. 6). It is applied to a greater or lesser extent by the Republic of South Africa, France, Sweden, Denmark and the United Kingdom.

The issue of the content of integrated reporting is the subject of the Framework of the International Integrated Reporting Committee - IIRC (Dumay et al., 2016, p. 167), and it should provide an accurate picture of the value and performance of companies through the publication of financial and non-financial information at different times intervals relevant to all stakeholders concerned. This type of reporting has yet to be regulated and harmonized, supported by the fact that many companies, despite the lack of obligation, still disclose on a voluntary basis reports on social and environmental performance and corporate social responsibility (Knežević, & Pavlović, 2019, p.128). The popularization of integrated reporting and the linking of diverse information in reports raises the question of revision of this information in order to assure its validity and credibility for all interested users.

Integrated reporting includes information relevant to current and future business related to strategy, management, financial operations, environmental impacts, human resources, investment development, local communities and threats and opportunities (Prošić, 2015, p. 68). Comprehensive information creates a good basis for making business decisions related to strategy improvement, risk management, increasing business efficiency and the like.

In addition to the numerous advantages of integrated reporting, certain problems have been identified in practice. Namely, it is very difficult to assess and connect qualitative information related to the environment and socially responsible business with the company's financial business. In addition, the problem of presenting intangible assets in the report remains (Prošić, 2015, p. 74).

One of the most popular ways to collect non-financial information is through the Balanced Scorecard (BSC). In response to contemporary management challenges, Kaplan Norton (Kaplan, & Norton, 1992, pp. 71-79) have developed a performance measurement model that includes non-financial variables in addition to financial ones. The model was developed through the following four dimensions (Krstić, & Sekulić, 2007, p. 181):

- the financial dimension evaluating the increase in value for business owners,
- consumer dimension that measures consumer satisfaction,
- dimension of internal processes that measure the efficiency of purchase, production, distribution and other functions in the company,
- dimension of learning and growth that measures the quality of human resources and their innovation.

In the company's bankruptcy prediction models, the authors used different non-financial variables. Some of them are presented in Table 1.

Table 1: Non-financial variables

Non-financial variables	Research study
Audit opinion indicator (1 if clean, 0 otherwise) Audit qualification indicator (1 if qualified, 0 otherwise) Number of years of financial statements in the database Number of consecutive years negative net income The number of consecutive years sales decline	Marais, Patell, & Wolfson (1984)
% Δ Industry output * Cash flow/Sales % Δ Industry Output * Total debt/Total assets % Δ Company sales / % Δ Industry output	Platt, & Platt (1991)
Auditor Auditor opinion Number of years of income drop Number of years of negative profit Number of employees	Leshno, & Spector (1996)
Complexity of capital structure defined by number of major classes of debtholders Degree of competitiveness as measured by the Herfindahl–Hirschman Index 1 if the fraudulent activity was observed, 0 otherwise 1 if resignation by top management took place around the filing date, 0 otherwise Ownership concentration: the total number of common shares outstanding divided by number of shareholders at the filing date Firm age: measured by months from incorporation date to the bankruptcy filing date	Barniv, Agarwal, & Leach (1997)
Gross domestic product growth	Bryant (1997) Li, & Faff (2019)
Manager Work Experience Company position on the market The technical structure of the building Organizational staff The competitive advantage of a company Market flexibility	Greco, Matarazzo, & Slowinski (1998)

Industry position Personnel and staff hiring policy Technology development and quality innovation Market niche/trend Pricing competitive advantage International competitive advantage Profit perspective Quality of management Relationship between labor and capital Working conditions and welfare facilities Industry reputation Growth potential	Park, & Han (2002)
Federal Budget/Gross Domestic Product Government Spending/Gross Domestic Product Money Supply 1 Money Supply 2 Short-Term Interest Rate Spread between Short-Term and Long-Term Interest Rate Consumer Price Index Trade Balance/Gross Domestic Product Current Account Balance/Gross Domestic Product Effective Exchange Rate Purchase Price of Crude Oil	Lam, (2004)
Retail Price Index (RPI) United Kingdom Short Term (3-month) Treasury Bill Rate Deflated	Tinoco, & Wilson (2013)
Number of employees	Stanišić, Mizdraković, & Knežević (2013)
Number of years since first registered as a corporate firm ΔGDP REPO-RATE (short-term interest rate set by the Swedish central bank)	Giordani, Jacobson, Von Schedvin, & Villani (2014)
Registered unemployment rate (urban areas) Total executive compensation (top 3 executives) Total director compensation (top 3 directors) GDP growth per capita	Jiang & Jones (2018)
Audit opinion Sum of accounting disclosures in the audit report Sum of general disclosures in the audit report	Muñoz-Izquierdo, Laitinen, Camacho-Miñano, & Pascual-Ezama (2020)

Source: Overview of authors

Macroeconomic variables can be found within the non-financial variables in the bankruptcy forecasting models. Jacobson, Linde and Roszbach (2013) examined the role of macroeconomic factors in bankruptcy prediction and found they were a significant determinant. Fejer-Kiraly (2015) believes that if there are economic changes in the time horizon in which the research is conducted and financial variables, it is necessary to include important macroeconomic variables in the bankruptcy forecasting model. In addition to accounting, market and statistical variables, Li and Faff (2019) introduced the most commonly used macroeconomic variable in the form of gross domestic product growth rates. In addition to also using the Gross Domestic Product Index as one of the variables, Giordani and others (2014) improved their model by introducing spline function (eng. spline functions) to increase the model's predictive power.

To build a model with high predictability and practical use, Tinoco and Wilson (2013) combined accounting variables with the market and macroeconomic variables. Nam and others (2008) have shown that the introduction of macroeconomic variables in an unstable environment is important for predicting the company's bankruptcy. However, they did not extensively analyze the impact of different macroeconomic variables on the company's bankruptcy forecasting.

In certain studies, the authors suggest that specific characteristics of the company be introduced as variables for bankruptcy prediction models. Rose (1992), for example, proposed raising a human resource variable (capital), under which high-efficiency and trained human resources reduce the risk of bankruptcy. Dennis and others (1997) believe the number of business segments needs to be taken into account. If businesses differ only in size, Beaver and others (2005) believe large enterprises are less likely to file for bankruptcy. In addition to looking at the height of Wu and others (2010), they add diversification as a characteristic important for predicting bankruptcy. Stanišić and others (2013) introduced an absolute variable measuring the number of employees in their bankruptcy prediction model in Serbia, concluding that increasing the number of employees jeopardizes the company's successful operation. Bankruptcy prediction models can also include variables that describe competitive advantage, management quality, number of years of functions and other non-financial variables.

The importance of non-financial variables in predicting bankruptcy of small and medium-sized enterprises was examined by both Altman and others (2010) and concluded that the introduction of non-financial variables increases the accuracy of model predictions by 13%.

Market variables for developing a bankruptcy prediction model

Although accounting data analyzes the company's operations, the reason for the dominance of financial coefficients based on accounting data in bankruptcy prediction models is not in absolute advantage in predictive power, but in the availability of data (du Jardin, 2009, p. 5.). On the other hand, market data cannot be provided for each analyzed company. Companies that are not public and whose shares are not traded on the stock exchange do not have market data. In underdeveloped and developing countries, fewer businesses opt to go public, making the availability of market information limited.

On the other hand, in developed economies, businesses collect missing capital by going to the stock exchange, and market data is usually easy to manage. Therefore, it is no surprise that models with market variables for predicting the company's bankruptcy were developed in the 1970s. Black and Scholes (1973) and Merton (1974) felt that market value influenced future expected cash flows, thus increasing the model's predictive power. However, rigorous assumptions such as normality of yield on shares and the existence of a coupon-free loan have been made to implement these models without distinguishing between different forms of loan (Saunders &Allen 2002; Agarwal &Taffler, 2008). By comparing models based on accounting variables and market models, the researchers came to different conclusions. While Agarwal and Taffler (2008) believe that accounting-based models are not inferior to market-based models, Hillegeist and others (2004) recommend using market-based models as providing significantly more information about bankruptcy prediction. Balcaen and Ooghe (2004) believe that if researchers use only accounting data, they imply the assumption that financial statements contain all the factors that influence the launch of the company's bankruptcy. However, because financial reports do not reflect both internal and external bankruptcy factors, Tinoco and Wilson (2013) believe it is necessary to include market data in the company's bankruptcy filing forecast. Bearing in mind that accounting variable-based models and market-based models have their advantages and limitations in the application, many researchers combined these two data sets with building a model with the highest predictive power (Shumway, 2001; Kealhofer, 2003; Oderda, Dacorogna, & Jung, 2003; Reisz, & Perlich, 2007; Campbell, Hilscher, & Szilagyi, 2008; Mai, Tian, Lee, & Ma, 2019).

Tian, Yu and Guo (2015) explored the relative importance of the different variables commonly used in studies. The authors concluded that variables based on accounting data are an effective supplement to bankruptcy prediction information based on market data on property values. Interestingly, the importance of accounting-based variables increases with an increase in the observation time horizon relative to market-based variables. Typically, the following market variables occur in bankruptcy forecasting models: market value versus book value of capital, yield per share over time, standard deviations of yield per share, etc. On the other hand, more variables based on financial statements should be included in the model in companies with excellent information asymmetry.

Statistical variables for developing a bankruptcy prediction model

In bankruptcy prediction models, authors apply statistical variables such as average, maximum, minimum, standard deviation, or variance of a particular financial account value or economic variable. Often, it is easier to handle high-value data and natural logarithm, which is an inverse function of the exponential function. The logarithmic transformation of financial indicators achieves greater accuracy of predictive models (Bradbury, 1988). Although the application of logarithmic function may increase the power of a given variable that is important for the process of regression (Altman, & Sabato, 2007, p. 343), there is a risk of losing the interpretive power of the variable reflected in the complex explanation of the variable trend, as well as the "business and economic logic of the variable itself" (Nikolić, 2014, p. 45). The table shows some of the studies that use the logarithmic transformation of the financial indicator to predict bankruptcy.

Table 2: Variables with logarithmic transformation of financial indicators

Variables	Research study
log(Total Assets/GNP price-level index)	Ohlson (1980)
log (Interest Coverage+ 15) log (Total Assets)	Frydman, Altman, & Kao (1985)
log (Tangible Asset turnover)	Karels, & Prakash (1987)
log (Total Assets) log (Interest Coverage) StDv (EBIT/Total Assets) StDv (Log(EBIT/Total Assets)	Leshno, & Spector (1996)
Natural Log of Total Assets deflated the GDP	Barniv, Agarwal, & Leach (1997)
log (Total Assets)	Korol (2013)
log (Sales) log (Total Assets)	Tian, & Yu (2017)
ln (Current assets/Current liabilities)	Gupta, Barzotto & Khorasgani (2018)
log (Total Assets) log (Sale) log (Price) log (Market Capitalization)	Mai, Tian, Lee & Ma (2019)
log (Price) log (Market Capitalization)	Cao, Liu, Zhai & Hua (2020)

Source: Overview of authors.

Standard deviation is a measure of the deviation of value from the arithmetic environment of the observed sample that can also be found as variables in the company's bankruptcy prediction models. Marais, Patell and Wolfson (1984) used as one of the variables the standard deviation of the company's common stock yield rate, while Leshno and Spector (1996) calculated the standard deviation of the business property yield rate measured through the ratio of profit before taxes and interest and business assets, and the standard deviation of the logic of the relationship between taxes and interest and business assets.

Conclusion

Most authors use financial accounts and financial statements as variables to develop bankruptcy prediction models. No analysis of a company's operations can be imagined without interpreting the value of financial accounts and financial statements. Nevertheless, the conclusions' quality is directly related to the credibility and quality of information presented in the financial reports. Adding to this, the timing and time period of financial reporting, numerous authors believe that this information alone is insufficient to decide on the company's operations and forecast future operations. For this purpose, non-financial variables related to innovation, quality of processes, products or investment in employee training are used more and more. Some authors believe that variables should be introduced in bankruptcy prediction models that will represent specific characteristics of the company, such as human resource variables, number of business segments, etc. Based on non-financial variables, relevant areas of action should be disclosed whose improvements directly positively affect financial indicators.

The most commonly used non-financial variable is the macroeconomic variable in a gross domestic product index. An unstable environment requires the introduction of other macroeconomic variables, such as inflation or unemployment indicators.

The loss of the power of predicting financial variables, according to many authors, is compensated by the use of market data that reflects both internal and external impacts that contribute to the initiation of bankruptcy proceedings. Combining variables based on accounting and market data contributes to the development of high-power prediction models. However, in countries with underdeveloped capital markets, it is not possible to collect adequate market data that could be used to develop and implement models.

For easier handling of high-value data in bankruptcy forecasting models, logarithmic transformation of financial indicators and balance sheet positions is used. This achieves greater accuracy of predictive models.

The paper provides a comprehensive overview of empirical research related to developing bankruptcy prediction models using different variables. By drawing attention to the pros and cons of individual variables and their impact on the power of prediction in certain economic circumstances, the paper can be helpful to researchers developing new models. Although many studies are used in the paper, insufficient attention is paid to predicting bankruptcy for companies operating in emerging markets, such as Serbian.

In addition to choosing variables, developing a high prediction accuracy model also depends on choosing a classic algorithm (e.g., Discriminatory analysis, logistical regression, neural networks, etc.). Although variables are most often represented by financial coefficients that describe the company's business, the choice of variables also depends on the economic environment in which the company operates, the development of capital markets, etc. By choosing different variables and different classification algorithms, different prediction accuracy results are usually obtained. Therefore, the subject of future research will be an analysis of the impact of different classification algorithms for developing high-power models of bankruptcy start-ups, as well as limits on their use.

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