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Models and Techniques for Evaluating Financial Performance and Predicting Bankruptcy

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Abstract- There has been a significant body of literature dedicated to the topic of bankruptcy prediction since the late 1960s. This literature seeks to analyse the causes of a company's inability to meet its financial obligations and to develop criteria for making predictions about bankruptcy. This study tries to identify the factors that are the best predictor of bank runs and to describe the main contributors to this type of economic crisis. Results show that both profit reports and the bankruptcy act's plausibility are non-linear. If the semi is ignored, developing sophisticated projections becomes difficult. The research also shows that precise model creation is next to impossible. Therefore, it is not undesirable to conduct further research into nonlinear models constructed with ad hoc variables**.**

Keywords— *Bankruptcy Prediction Models, Financial Health, , financial ratios, Probability*

I. Introduction

1.1 Background

When we talk of a company's "financial health," we're referring to the company as a whole, not just its current financial situation. If a company can meet its financial commitments while still being profitable, it can be said to be in terms of profitability. Organizational financial health is comprised of three pillars: profitability, liquidity, and stability.

Prediction models are a relatively recent approach of financial analysis that arose out of efforts to detect signs of business insolvency at an early stage. Indicators are used to provide an advance indication of a commercial entity's poor financial development (forecasting) based on historical performance. These models are based on the idea that a company on the verge of bankruptcy will have displayed a number of discrepancies and warning signs in its financial health over a period of time (problems with conversion rate, net capital investments, revenue growth, and so on) in comparison to a financially sound company. Similar to how no method for investment appraisal prediction can be deemed 100% reliable, it is also not possible to include characteristics that are specific to the environment of a business being analysed.

II. REVIEW OF LITERATURE

2.1 Bankruptcy Prediction Models

2.1.2 History

Historiographically speaking, developing models that can accurately predict the bankruptcy of a business entity can be broken down into a few distinct periods, each of which is characterised by the application of a different tool for the advancement of bankruptcy prediction models. The first investigations were conducted in a straightforward financial analysis, which was based on a financial ratio analysis (an analysis with a single dimension). This research compared the values of prosperous and unsuccessful corporate units. The publication of a study in 1930 by the Bureau of Business Research titled the Study of Indications of Failing Manufacturing Business Entities was one of the most important and landmark years in the history of the American economy. The research aimed to identify the fundamental features of failing commercial enterprises by analyzing 24 variables across 29 different business entities. After that, the values of the indicators for each business entity were compared with the average values of those indicators. This allowed for the identification of disparities, fundamental features of failing business entities, and trends. Merwin released the findings of his research in 1942, and it was focused on the operations of small company enterprises. According to the research findings, the fundamental warning indicators start to materialise about four to five years prior to a company's financial collapse compared to successful and unsuccessful commercial units. Chudson (1945) made a groundbreaking discovery in the annals of the history of economic pressure modelling when he discovered that it is possible to observe an intrinsic properties of surveyed values of metrics within the context of a particular industry, the size of the business entity, and the profitability of the business. He labelled the phenomenon "clustering of ratios" to describe it.

It's possible that, from a methodological point of view, the years 1930 to 1965 shouldn't be regarded to be a period for the creation of bankruptcy prediction models; instead, this period was more or less a financial examination of ratios. Beaver's research (1966) was the first to offer the bankruptcy prediction upon use of a single reaction. This study is regarded as an important milestone since it was the first to do so. This research may be considered the second generation in the development of prediction models, covering the period up to the 1980s. At the end of his research, Beaver suggested that in the future, consideration should be given to performing simultaneous evaluations of many indicators at the same time. Altman (1968), who triggered a modest revolution from the perspective of corporate entities' financial pressure projection, caught up this necessity immediately after it was brought to his attention. When considering the use of a multidimensional analysis, Altman's model is the first bankruptcy prediction model ever developed.

The work that Altman (1968) did provided as inspiration for other academics and researchers who focused primarily on the limiting hypotheses of panel data from a scientific standpoint. They did this in response to Altman's work. The primary response that they came up with was the creation of conditional probability models, the majority of which were based on the logit and probit methods. Ohlson's model (1980) was the first to use logistic regression (logit). One of its advantages was that it did not need the fulfilment of fundamental statistical preconditions like linearity or homoscedasticity amongst others. In their research, Balcaen&Ooghe (2008) review models over the previous 35 years up to 2006. They show that a particular model has outlasted the capacity of Altman's model to make predictions. The Zmijevski model from 1984 was created similarly; it employed probit analysis to construct a model to forecast bankruptcy. These two approaches continue to be used, but often with a variety of modifications.

Zopounidis, et al. (1998) research includes various other methodologies and models employed throughout the 1980s and 1990s. Some authors emphasise the works of Frydman et al. (1985), who used a recursive distributed algorithms approach, and Gupta et al. (1999), who used a matlab/simulink environment to solve the commercial business failure prediction problem. Survival analysis (Luoma&Laitinen, 1991), expert methods, and the multi-factor model were also used in other studies (Vermeulen et al., 1998). According to the literature (Vermeulen et al., 1998). Decision management was also mentioned among the various methods used by authors including Zollinger (1988), Product and product (1987), and Siskos et al (1994). (1994).

Opportunities to leverage information technology & machine learning emerged in the late 1990s. That required tapping into the potential of smart systems, an area where study is ongoing and far from complete. For the purpose of predicting the insolvency of businesses and other institutions, Kumar & Ravi (2007) give a comprehensive analysis of regression models.

Economists and experts from across the globe are tasked with finding the best bankruptcy prediction model. While many alternative models have been developed using diverse methodologies to attain the best outcomes, it is still difficult to anticipate bankruptcy risk since organisations are becoming more global and more complicated (Kovacova, Kliestik, 2017).

Much attention has been paid lately to studies that attempt to anticipate bankruptcy. It is now conceivable to see some form of hybridization that incorporates parts from the different methodologies, generating a single model that combines their merits when it comes to bankruptcy prediction. Statistical approaches are simpler when compared to methods based on machine learning & artificial intelligence, but there are also drawbacks. In addition, models role of accounting models and data models may surely be established as clear and appropriate for management choices and corporate practise.

2.2 Definition of bankruptcy

According to Tinoco and Wilson (2013), bankruptcy prediction models should not rely on the legal definition of bankruptcy. That a company's financial issues do not have to have started on the day of bankruptcy is the basis of their claim that insolvency might endure for a longer time than is required by law. Authors also say that owing to significant variations in bankruptcy laws during model evaluation, such as recording financial information from the last five years, findings may be inaccurate. This might diminish the model's capacity to forecast future events. Balcaen and Ooghe (2008) argue that a legal definition of bankruptcy has the following disadvantages:

- Dictionary concept of bankrupt differs according to a nation for which the bankruptcies proposed methodology was built. Suppose we want to analyze a definition of bankruptcies in research from other nations. In that case, each region has own distinctive modifications of constitutional system when it refers to bankruptcies.
- The time of legal debt fails to match the real date of bankruptcy. As per legal framework, there may be a large variation in time between real bankruptcy versus insolvency.
- It is also feasible that a corporate organisation displaying symptoms of being bankrupt may not have to file bankruptcy officially.
- Possibilities opened up in the 1990s thanks to the use of computer science and artificial intelligence. That required making use of intelligent systems for which study has been ongoing right up to the present day but is far from complete. In their paper, Kumar and Ravi (2007) give a comprehensive evaluation of regression models, an extensive survey of publications applying statistical methodologies and algorithms used for financial forecasting of commercial companies and institutions.

When a company is having financial troubles, it may be described by various terminology that might make it difficult to evaluate the results, including financial hardship, financial problems, a company's financial health, bankruptcy, liquidation, and dissolution. Financial trouble and bankruptcy must be distinguished according to these criteria.

Altman & Sabato (2010), in line with Basel II, describe economic problems as the obligor being more than 90 days late in repaying the bank for significant credit extended to the obligor. For instance, a company is in financial distress if its interest and debt service costs exceed its earnings before interest and taxes (EBITDA) for two consecutive years. Similarly, if a fund from long-term liabilities is less than the amount necessary to repay its long-term outstanding debt, the company is insolvent (Tinoco, Wilson, 2013). When it comes to avoiding money problems, most definitions point to a steady stream of cash as a necessary precondition. Numerous financial hardship categories could not apply to Central and Eastern Europe because of the region's undeveloped financial market. This is the case because current stock and bond market values are included in.

When a person or business cannot pay its debts in the usual course of events, bankruptcy may be filed to protect creditors' rights. Distribution of assets to creditors and, in most cases, release from additional financial commitments are primary goals of bankruptcy processes. Bankruptcy may be declared involuntarily by the debtor or by the creditors (involuntary bankruptcy).

Depending on the scale of the fail and the kind of failure, the impact on stakeholders might vary greatly. The proliferation of business failures of all kinds has led to adopting a slew of new definitions and conceptualizations of failure. Research on "enterprise failure prediction" has grown significantly during the last 35 years. Based on publicly accessible data and statistical methodologies, several academic research has been devoted to the quest for the best business failure prediction. (Kliestik, Kocisova, and Misankova, 2015).

As part of our long-term financial health prediction study in Slovakia, we are also trying to uncover the prerequisites for a company's failure that arise from legal and accounting factors. With the help of three financial ratio limit values, we developed a universal standard for classifying a company as either successful or unsuccessful: R - return on assets (net); L - total liquidity; Z - indicator of financial independence. We named these indicators summarise indicators while considering the current legal regulatory requirements of the Slovak Republic that specify conditions for an enterprise's failure.

2.3 Bankruptcy factors and explanatory variables

2.3.1 Bankruptcy factors

As part of our long-term financial health prediction study in Slovakia, we are also trying to uncover the prerequisites for a company's failure that arise from legal and accounting factors. With the help of three financial ratio limit values, we developed a universal standard for classifying a company as either successful or unsuccessful: R - return on assets (net); L - total liquidity; Z - indicator of self sufficiency. We named these indicators summarise indicators even considering the current legal regulatory requirements of the Slovak Republic that specify conditions for an enterprise's failure.

As a result, financial difficulties may be traced back to several different factors. The challenge, however, is in identifying the variables that could represent these aspects. Each of the causes mentioned above cannot be confined to a mere, quantifiable factor. What are the elements that serve as indications of these weaknesses?

As most of these effects may be predicted over time, they may be possible to be avoided. In other words, practically all of them may be detected by a careful examination of finance and accounting records (Pérez, 2002). Therefore, financial papers serve as the primary source of information for developing bankruptcy models. When it comes to predicting a company's chance of failure, financial indicators alone aren't enough; other factors, whether they can be assessed, must be considered.

2.4 Variables that best reflect company failure

- The first category focuses on the company as a whole and includes both financial (balance sheet or income comment variables) and company-specific variables, such as those that reflect the organization's structure, management, strategy, and products;
- The second category examines the firm's external environment in more detail through general indicators, and, finally, category focuses on the company's products and services directly.
- According to the market efficiency theory, a company's stock price or return may be a proxy for its economic condition since it represents future projected cash flows. As a result, several researchers propose utilising this proxy to supplement or replace other forms of data.

These three areas are the origin of all of the explanatory variables that are employed in bankruptcy models. It is possible to design them by using a variety of facts, as seen in table 1.

Table 1: Typology of explanatory variables commonly used by bankruptcy prediction models

Variables	Frequency (decreasing order) of use in the 190 studies
The financial metric (ratio of 2 financial variables)	93%
Ratios or financial variables may be used to determine statistical variables such as the mean, standard deviation, variance, logarithm, confirmatory factor scores, etc.	28%Financial market data, such as a company's balance sheet, income statement, or other financial reports.
Variation is a constant (growth with time of a ratio or a financial variable)	14%
Variable that has nothing to do with a company's financial health, such as a company's size, industry, or location.	13%
Market variable (ratio or variable related to stock price, stock return)	6%
Financial market data, such as a company's balance sheet, income statement, or other financial reports.	5%

Due to the potential employment of many kinds of variables at once, the total is likely to be more than 100.

2.4.1 Financial ratios

An important first form of variable is a financial ratio, which shows how one item on a balance sheet or income statement compares to another in terms of value. Using financial data from diverse organisations necessitates financial ratios to ensure that the size impact is taken into account (Salmi and Martikainen, 1994). In fact, only if the organisation's size is carefully analysed can financial data be effectively comprehended; this is especially true when statistics are compared. In this way, ratios aid in the standardisation of data, making it feasible to perform the categorization and comparison activities necessary for any prediction process. There are several instances when ratios do not consider the effect that size has because the core idea behind ratios rely on a proportionate that is not always brought forth between the numerator or the denominator (Lev and Sunder, 1979). According to Gupta (1969), as a company expands, All of its profitability, liquidity, activity, & liquidity ratio (fiscal deficit holdings, present costs and expenses debt, current liabilities assets) improve. Other activity ratios (such as asset turnover

& cash velocity) also improve. Horrigan (1983) argued that the fact that firm size cannot be arbitrarily limited is really a boon to the industry. This is due to the fact that a company's size may be a significant factor in explaining several aspects of its financial performance. Prediction models, however, should not be constrained by the under- or over-representation of a certain category in a sample of businesses (small vs. large companies. This limitation however, financial measures continue to see widespread use in assessing business performance. A staggering 93% of the 190 studies we looked at make use of ratios, whereas just 7% rely on any other measures of significance.

More than half of these studies employ solely ratios in their models, and nearly seventy percent use ratios either alone or in combination with another kind of variable.

2.4.2 Other types of variables

While ratios have an important influence, five additional factors play a secondary function but are not insignificant. Means, standard deviations, variances, logarithms, and other mathematical and statistical functions are examples of "statistical variables," which are second on our list. Factor analysis scores are also included. The logarithm of "financial variables" is one of the most common standardisation procedures, and these calculations are often employed to do so. "Total assets" has been one of the factors having genuine discriminating power since 1968, according to Altman (1968).

The third most often used category, "variation variables," refers to variations in a ratio or fiscal variable from one year to the next. This dynamic picture of failure shows that the cycle of fail may take upwards of one shape and that trends or variations alone can disclose the stage of the project in which the business is now situated.While a static representation may identify imbalances and display their direction, a dynamic one can reveal the direction of such imbalances.

"Non-financial variables" occupy the fourth spot on the list. Qualitative or quantitative qualities of other enterprises, or their surroundings, are also included in this category. A approach to widen the characteristics of failing to include those that cannot be incorporated in associated with excessive but play a substantial influence has been adopted. "

Fifth, "Financial market variable" reflects the worth of enterprises as judged by financial markets, based on stock prices or returns.

There are also "financial variables," particularly those used to calculate financial ratios, such as liquidity and asset and turnover variables, which may be utilised alone without being standardised.

2.4.3 Financial ratios: the most commonly used variables

For the most part, financial measures are utilised because of our economic nature, not just their precise predictive accuracy. Non-accounting data, on the other hand, may sometimes be gathered exclusively for certain kinds of corporations or not at all; for example, financial markets data are only accessible for publicly traded companies.

There aren't enough research looking at the predictive power of these factors to account for their widespread usage. According to Back et al. (1994), the use of financial ratios itself may outperform common financial variables when it comes to forecasting (assets, debt, income). Related to financial industry variable-based and ratio-based models, Mossman et al. (1998) found that the ratio-based models had somewhat superior outcomes. Three models were examined to see whether non-financial factors, either alone or in combination with financial ratios, could provide better predictions than that of a model based only on ratios, according to Keasey and Watson (1987). The ratio-based model was somewhat more accurate than the model defined as non factors. The financial and non-financial signals model had better outcomes than the other models. Lussier (1995) attempted to construct an insolvency model using qualitative factors to define both company leaders and their business were unsuccessful, since the model's accuracy in identifying sound businesses was only 73%, while its accuracy in identifying insolvent enterprises was only 65%. When comparing two models, Atiya (2001) found that a ratio-based model was marginally more accurate than a ratio + financial industry variable-based model. Environmental influences on business were taken into consideration by Tirapat&Nittayagasetwat (1999) in their model of financial ratios on macro-economic variables. The accuracy of its forecasts was less than 70 percent. When it comes to "variation variables," Pérez (2002) conducted a study of a small and medium businesses and found that absolute numbers outperformed data on the fluctuation of financial factors. Absolute ratio values are stronger predictors than changes over time, according to Pompe&Bilderbeek (2005), who also found similar results.

The popularity using financial ratios is currently unknown, however we may speculate as to why they are so popular. Due to the great forecasting abilities of ratios, other factors are ruled out because of their high cost.

2.5 Selection methods

2.5.1 Search procedure

As previously said, not all situations are amenable to a thorough investigation. It is preferable to focus on a smaller portion of the search area for non-monotonic assessment criteria and vast search spaces (for n variables, 2n - 1 potential subsets). In contrast, if the monotonic argument is confirmed, it is conceivable to go farther. According to the research, there are several ways to classify methodological approaches. Breaking them down as follows families, Dash et Liu (1997) propose:

In cases where the criterion for evaluation is monotonic, "complete" methods can determine the best answer. In order to prove that the search is both "complete" and "non-exhaustive," a heuristic tool is used to restrict the keyspace without reducing the likelihood of finding the best subset according to the evaluation criteria (Branch and Bound) utilised in the search.

• "heuristic" or "sequencing" approaches may help loosen the monotonicity requirement imposed on the assessment criteria by the aforementioned methods. Some begin by trying a small number of situations at a time (ahead search), while others begin by trying all possible conditions and then eliminating them piece by piece (back search) (backward search). However, they provide inferior results since they can only forward-think and forward-look at the issue area. If a certain

one is selected, it can't be changed anymore (nesting). Although computing time rises as the search space expands, this procedure may be improved by using certain techniques, including the "Plus r – Take Away r, drifting methods...", which alternate forward and backward steps (stepwise).
• "Random" Methods: In contrast to the previously discussed procedures, the outcomes of these methods are highly context-specific. They start with a shuffled deck of variables and then search using either a sequential method like Simulated Annealing or a stochastic one like genetic algorithms. You can read about both of these tactics up top.

In order to assess the global characteristics of a set of variables, nonmonotonic conditions need for either a sequential or random method.

2.6 Evaluation criterion

A subset containing variables must be assessed once a search technique has narrowed it down to a few. It is the capacity to distinguish between different groups that will be evaluated in a classification job such as those we are working with. Hence, a standard by which we may eventually assess and choose amongst distinct groups is required to arrive at a final solution. Evaluation techniques are divided into two groups by John and colleagues (1994): those that depend only on intrinsic qualities of data (filter methods), and those who do rely on the inductive algorithm's performance when employing variables that are being assessed (wrapper methods). The following are the standards by which various techniques are judged:

- This means that each criterion represents a distinct kind of measurement. Dependent criteria: with these criteria, the initial set of variables can be reduced to the smallest subset of variables of the same discrimination ability as the initial set of variables;
- distance measures: these criteria can be used to determine how much a variable contributes to the discriminatory treatment among both groups (Mahalanobis distance, Battacharyya distance, Wilks's lambda). For example, those variables that result in the lowest generalisation error will be considered for inclusion. To get decent results, you need a lot of computational power, so wrappers are so useful.

Independent criteria, such as Wilks' lambda or probability statistics, are often employed to pick variables in classification issues like this work.

2.6.1 Stopping criterion

A selection process may go on forever if there is no way to halt it. Interrupting a search may be done for a variety of reasons. When these criteria are used, they usually refer to the most variables, a predetermined limit on repetitions, no progress after adding or removing variables, and achieving maximum accuracy in prediction (in other words, an acceptable generalisation error). There are several computer techniques and statistical tests that go into these evaluations. Once it is determined that there is no more information to be found, the search process ends.

2.7 Selection methods used to build bankruptcy prediction models

Researchers often employ a two-step method to choose the "best" variables to include in their cash burn models. There are many variables to choose from at first, but only a few are selected for statistical reasons, and this is typically the case.

Initial variables are often picked at random from a list of several hundred depending on how frequently they appear in the research or how well they have predicted outcomes in prior research. when scholars in the 1930s started looking at financial ratios to anticipate company failure and when multivariate statistical techniques were used in bankruptcy prediction, this "historical" collection was developed based on their pioneering work. following this are the likes of zmijewski (1984), zmijewski (1996), and zavgren (1999). (1985). as a result of this effort, a complete collection of important bankruptcy predictors has been developed, supplemented throughout time by other indicators, whether or not they are accounting-based assessments of a company's financial health.

3. OBJECTIVES

- Identify the most important causes of financial failure.
- To examine the factors that are thought to be the greatest predictors of bankruptcy.

4. CONCLUSION

A number of inferences may be taken from this investigation. For starters, severalresearch have looked at whether regression or classification approaches may be used to create bankruptcy prediction models. As a result, other issues, such as variable selection, have been overlooked, resulting in a lack of attention to these other issues. We now know a great deal about how modelling approaches work and how they might be used. Furthermore, we know that a model's accuracy is influenced by the model's inherent qualities, its fit, and the parameter selection strategy used in its creation. Accordingly, it is important to point out the disparity between the selection procedures used to pick the variables used in various classification or regression approaches and those advocating comparing the outcomes of these techniques. This topic should be given more attention. The second point is that numerous research suggest that financial ratios and the likelihood of bankruptcy have non-linear behaviour, making it difficult to create reliable models without accounting for them. Hence, further research into nonlinear models using custom-made variables might be beneficial.
Finally, beyond the problem of prediction, selection procedures should be investigated in areas other than those connected to model creation to use the potential they provide. Such an investigation might help us better understand the elements that lead to failure, such as whether "strong," sample- and method independent statistics accurately represent failure causes. It would, in short, assist explain the dynamic nature of financial failure by analysing failure from a variety of aspects and identifying trends.

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