# EVALUATION OF THE FINANCIAL STANDING OF BUSINESSES IN A CERTAIN SECTOR OF THE NATIONAL ECONOMY

Nadezhda Krasteva[1,a], Marek Nagy[2,b*]

[1]South-West University Neofit Rilski, Faculty of Law and History, 1 Georgi Izmirliev Sq., 2700 Blagoevgrad, Bulgaria

[2]University of Zilina, Faculty of Operation and Economics of Transport and Communications, Univerzitna 1, 010 26 Zilina, Slovakia

[a]nkrusteva@law.swu.bg, [b]marek.nagy@stud.uniza.sk

[*]Corresponding author

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**Abstract:**

*Research background*: A company's operation, revenue and costs, profit and loss at the end of the economic period are all impacted by its financial situation. Today, however, there are a lot of companies that fail because they are unable to achieve their objectives, compete effectively, or both.

*Purpose of the article*: The major objective of this research is to describe the prediction models that were developed for the chosen sector of economy, to examine the financial stability of the enterprises in that sector, and to confirm their predictive power in Slovak market conditions. The economic sector NACE H (transportation and storage), the second most important section in the investigated environment, was selected to prove the importance of the financial health prediction.

*Research methodology:* In the manuscript, four foreign and domestic models were used for the analysis of financial health, four of which were intended directly for the observed sector of the NACE H (transportation and storage). The results of the analysis, using prediction models, were individually described for the monitored pre-pandemic years 2015-2019. Selected prediction models were applied to the analysis using ROC curves after doing a financial health analysis with them. We identified and detailed in greater depth which models should continue to be employed in the investigated sector based on the results that were obtained.

*Findings & Value added*: The discriminant analysis model produced the poorest results for businesses operating in Slovakia in the SK NACE H sector. On the other hand, they acquire a high qualifying ability. The additional value of this study may be seen as an intriguing comparison of forecasting models in a unique industry that is essential to daily life and, as a result, it can greatly assist businesses in this industry in their forecasts and analyses of their financial health and protect potential investors and stakeholders against unexpected losses.

**Keywords:** credit models, company prosperity, Slovak prediction models, discriminant analysis

**JEL Classification**: D22, G33, L25

## 1. Introduction

Every single company that is started with good intentions does so with the hope of prosperity that will help the business stand out from the competitors and advance him in the market. Not every business is successful in achieving this objective. Many evident but sometimes surprising factors have an impact on the corporate success. When a company's aims are not sufficiently achieved because of a lack of profitability, it starts to lose its value and, in the worst situations, go bankrupt (Ionescu, 2021). For the aforementioned reason, it is essential to do a financial analysis of the business at specific intervals or before making decisions that will have a long-term effect on how the business operates (Hamilton, 2021). It is crucial for the business to understand which phase it is in and take action to reduce or eliminate negative effects depending on the findings of the analysis (Dawson, 2021).

The main objective of this paper is to characterise prediction models that were developed for a particular economic sector, in this case NACE H (transportation and storage), to examine the financial health of businesses in that sector, and to confirm the ability of the models to predict future financial development of enterprises in this crucial sector.

We included knowledge from literary sources, expert scientific papers and publications, and Slovak Republic-specific regulations into our investigation. In order to summarise individual outcomes for the models we employed in different years, we used contingency tables in the analysis. The models were applied to businesses that operated on the market in the pre-pandemic period, from 2015 to 2019, to avoid some misinterpretations in the study outcomes. The multinational database Orbis was used to provide information, indications, and financial data about businesses. After confirming that the company's financial condition was correctly predicted, we conducted a study utilising ROC curves to gauge the degree of classification ability. Four models with the highest proportion of matches to the actual financial situation of the organisation were subjected to ROC curve analysis.

The paper is divided into several sections. We discuss the historical progression of the requirement and demand for prediction models in the market for businesses in the literature review section. We emphasise the value of doing routine financial analyses of the business and the consequences of doing so. When applied to businesses operating in Slovakia, we attempt to compare international and Slovak models to some extent. After being initially verified in the theoretical section, relevant models were then applied in Slovak conditions. For the examination of financial health of the enterprises in the dataset, we employed two international models, five local models; four of them were specifically designed for the transportation and storage sector. For the monitored years 2015–2019, the findings are presented per individual prediction model. Using the ROC curve analysis, we identified and detailed in greater depth which models should be used to predict the future financial development of enterprises the most accurately. The results are discussed in the context of other studies published worldwide. Conclusions summarizes the most important outputs, portrays the limitations of the study and future research challenges.

## 2. Literature Review

The long-term objective of almost all managers is to guide the business toward a defined goal. According to Klepac et al. (2016), the company's subsequent goals are formed using its financial goals as a foundation. Setting objectives is largely influenced by the type of business, the location of the present and future market conditions, and the legal structure of the enterprise. Maximizing the market value of the business over the long-term horizon is one of these objectives and is of crucial importance (Grofcikova, 2020). Financial analysis, according to

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(Knapkova, 2013), entails a thorough assessment of the business and the following identification of numerous flaws. These flaws include the failure to pay debts off in a timely manner, the improper allocation of money and assets, or the prudent use of assets (Sumani et al., 2020). Different techniques can be used to do financial analysis (Karpavicius et al., 2019). Each technique has a purpose, as well as advantages and disadvantages. These analytical techniques include ratio analysis, vertical analysis, horizontal analysis, bankruptcy models, and credit models (Ma et al., 2020; Akhtar et al., 2021). Vertical analysis, is used to indicate the percentage share of capital and asset (Gajdosikova et al., 2022). As a consequence, it indicates how well or poorly the corporation treats its capital and assets. Horizontal analysis maps distinct balance sheet items throughout a certain time period. The outcome is a percentage change over the year or time frame under consideration. Creditworthiness is characterised by Marinic (2007) as a specific assessment-rating. According to the rating, the firm belongs to a specific class of businesses, from which it is possible to determine its creditworthiness and the danger it poses to creditors and investors (Silaghi, 2018). In terms of a true appraisal of the firm's present situation and its ability to make payments in full and on time, the evaluation of the company using the credit rating model is effective (Lazaroiu et al., 2021). Rejnus (2014) outlines the significance of bankruptcy models and explains its foundation as the capacity to alert the user or analyst in good time to the possibility of bankruptcy in the future. The models are founded on the observation that businesses exhibit evidence of unprosperity prior to bankruptcy for a specific period (Sumiati, 2020), which may be tracked using certain indicators. They were created using information on firms that have already filed for bankruptcy as well as a search for shared characteristics (Jankelova et al., 2021). An evaluation coefficient, the outcome of financial analysis using the bankruptcy model, is expressed from a predetermined equation for each model, where fixed constants are or can be multiplied by specific indicators (Tasaryova et al., 2021). The amount of the company's bankruptcy risk is then indicated by the evaluation coefficient that was generated.

In 1968, Altman (1968) built his first model. In the financial sector and the use of discriminatory functions, it was revolutionary. The Altman model was developed for American economic conditions, therefore its applicability to the current state of our economy is in doubt, and the conclusions drawn from its application should be treated with caution (Zavadsky et al., 2019). According to Kalouda (2015), it is noteworthy to declare that our firms work to minimise the value of their economic outcome, or profit, in comparison to American ones. Tax base reduction and tax optimization support this action (Pereira et al., 2021). The converse is true for US corporations, which attract potential investors with their extremely successful operations (Akgun et al., 2021). But over time, this model has been strengthened to the point that it can now be applied successfully in Slovakia and the Czech Republic's economic environments (Hlawiczka et al., 2021). The Beerman's discriminant function, was developed specifically for manufacturing and craft businesses (Beerman, 1976). It is strongly discouraged from being utilised for financial analysis of businesses that prioritise sales. According to Michalkova et al. (2021), the goal of Beerman's discriminating function was to create a linear function by combining ten different indicators. The answer to this equation is the value, which represents the company's current status. According to this function, the organisation is more creditworthy the lower the value (Pham et al., 2020). The Neumaiers developed the discriminating feature for local Czech businesses known as IN indices (Neumaier et al., 1995). The model was originally known as the IN-Confidence Index when it was first developed. The model was modified throughout time to reflect changing economic situations, leading to the creation of other variations (IN05, IN01, and IN99). The IN95 Index, where the value of the enterprise is determined after being entered into the calculation, is the most well-known and widely used in

Visegrad environment. After that, the value is evaluated using three intervals. The likelihood that the firm faces financial difficulties increases as the value decreases (Xu et al., 2021). The building of a model that can accurately estimate one qualitative variable from numerous independent factors is the aim of discriminant analysis (Lajtkepova, 2016; Bui et al., 2021). Stefko et al. (2020) explored the potential use of Data Envelopment Analysis (DEA) to forecast a corporate financial health. They were founded on the idea that broad forecasting models are predicated on very specific financial data. A sample of businesses in a stable environment—the Slovak heating industry—was chosen and 343 businesses were included in the sample. The analysis revealed that the use of DEA to forecast financial health is just as effective as employing a model that is appropriate for the current company environment (Stryckova, 2017; Sener et al., 2021). Nurcan et al. (2021) concerned with the forecast of financial health in today's economies. They attempted to develop a model based on the use of logistic regression from conventional statistical techniques and the so-called DEA (Data Envelopment Analysis). They choose businesses that traded on the Istanbul Stock Exchange between 2014 and 2016 as a representative sample. The study's conclusion, which confirms the high qualifying capacity of the model based on logistic regression, was the outcome of the research. They used the DEA (Date Envelopment Analysis) approach to compare the model with the previously reported forecast of financial collapse. However, they continue to affirm that the DEA (Data Envelopment Analysis) approach is still a common way for a business to determine which areas need improvement. Hooda et al. (2021) used an analysis of Indian enterprises and twenty-eight financially critical factors to estimate possible hazards and business success, or profitability. The information utilised was gathered between 2016 and 2017. Up to 70% of firms were accurately identified by the given model for certain years. It is not feasible to use every single prediction model to every form of business due to the diversity of economies in the global environment (Grundy et al., 2020). According to Kliestik et al. (2019), it is necessary to develop particular models that are designed for exclusive nations or classes of economies. The model's categorization abilities can be impacted by a variety of factors, including the model's size, business emphasis, and operational location (Chudik et al., 2017). For the Slovak Republic, a number of models were created, some of which were then used to the analytical portion of the study. It was required to apply several mathematical and statistical techniques, as well as many variables, to develop the models (Valaskova et al., 2021). In order to forecast a corporate financial health, discriminant and linear regression-based prediction models are often used. Gepp et al. (2015) explored the potential of decision trees by examining how different market conditions affect survival models, cost ratios, and prediction ranges. According to the findings of this study, employing decision trees and survival models is a viable alternative for accurately forecasting a company's financial health (see also Cam et al., 2021 or Furlong, 2021). The attempt is to compare several models while keeping in mind the primary goal of the project. First models were created for use in nations other than the Slovak Republic and second models were created specifically for use by Slovak companies. In addition to familiarising us with the key models employed in the analytical portion of the job for estimating the indicated financial position of the firm, the study gives us a certain methodological development of the need to know the financial status of the organisation.

## 3. Data and Methods

Every sensible business owner starts out with the intention of becoming prosperous. However, based on the established corporate life cycles, we are aware that the company eventually hits a crisis point (Valaskova et al., 2018). To survive in the competitive business climate, the corporation is required to make adjustments or spend money investing in new products or services. If the business fails, it moves on to the final step of its life cycle, which is the termination of its business activities (Xavier et al., 2020). The approaches and strategies for a corporation to avoid the last stage in time through analyses of financial health using prediction models with a focus on a particular section will be the subject of the analysis.

Data from the company's past and current situation are required for any analysis to be performed. It is required to gather and collect pertinent financial information about the organisation to conduct the analysis (Cao et al., 2019). We are referring to a profit and loss statement, a balance sheet, or a cash flow statement in the context of a business entity (Alexy, 2005). We concentrated on a section H - transportation and storage - as part of the analysis and application of insolvency and creditworthiness models and verification of the classification abilities of these models. 836 enterprises operating in the Slovak Republic between 2015 and 2019 formed the sample for financial model analysis and implementation. The minimum value of total assets of enterprises in the sample throughout the monitored period is €200,000. The limitation was set to gather the enterprises with similar financial background. The international Orbis database, which has all the information we require for conducting analyses of businesses and the targeted economic sector, served as the primary data for conducting analyses utilising prediction models. The next phase involved removing extreme and outlying values from data collected from businesses and removal of those enterprises with not available information needed to calculate the ratios of financial activity and performance. We obtained the final sample of 601 enterprises, the representation of individual enterprises by their size is presented in the following table (Table 1).

*Table 1. Number of enterprises based on their size*

| **Size of enterprises** | Small | Medium-sized | Large | TOTAL |
|---|---|---|---|---|
| **Amount** | 85 | 424 | 92 | 601 |

*Source: own calculations*

The success of determining the bad financial status (financial distress) of an enterprise is one the most important steps of the analysis. The equity-to-liability ratio is used, which helps identify a company in crisis once the ratio is less than 0.08 (the determination of this value is set by the Slovak Commercial Code).

It is required to calculate specific metrics to identify firms that are generally not doing well (Wasiuzzaman et al., 2019). In this paper, a non-prosperous firm is one whose total assets are smaller than the total of its short and long-term obligations, or one for which both of the following relationships hold true, according to Kliestik et al. (2019). The following should apply:

$$\frac{Current\ assets}{Short-term\ liabilities} < 1\ and\ EAT < 1 \tag{1}$$

EAT (Earning After Tax) must be also smaller than 1. In 2019 it is:

$$\frac{Equity}{Liabilities} = 0.08 \tag{2}$$

The value of 0.08 is established depending on the year in which we assess the company's financial standing. In order to identify which of the 601 firms in the SK NACE H sector are wealthy and which are not, we applied the algorithms to the complete sample of enterprises. The following tables for the specific years we are analysing show the outcomes of applying the algorithms.

*Table 2. Number of prosperous and non-prosperous enterprises (2017-2019)*

| State of the business | 2019 | 2018 | 2017 |
|---|---|---|---|
| Prosperity/Non prosperity | 536/65 | 549/52 | 559/42 |

*Source: own calculations*

We may infer from the computations that there were marginally more prosperous and less lucrative firms. An average of 92.51% of the enterprises from the chosen sample were classified as successful for the three years between 2017 and 2019, while 7.49% were classified as non-prosperous. In the next section, we'll compare the actual situation of businesses with predictions made about their financial prosperity based on the mathematical prescriptions of carefully chosen prediction models:

**Altman's model**

Five ratio indicators must be understood in order to use Altman's model to assess a company's financial standing. To demonstrate that Altman's approach is inappropriate for Slovakia's or any other nation other than the USA's economic climate, we used it to check the health of firms (United States of America) (Lee, 2019). The financial accounts of the firms, which were available via the Amadeus database, had all the information that was required. Altman identified three potential scenarios, or the states of the organisation in which it may be positioned, after including them into the formula used to calculate the so-called Z-score.

We are discussing the bankruptcy zone, which is defined as the Z-Score falling below 1.81, the grey zone, which is defined as the Z-Score falling between 1.81 and 2.99, and the prosperity zone, which is defined as the Z-Score falling above 2.99. We separated the aforementioned bands and the zone into two bands in order to effectively assess the analysis using the Altman model. both the bankruptcy zone and the wealth zone. Businesses that achieve a Z-score of more than 2.395 fall into the zone of prosperity. Businesses who have a Z-score of less than 2.395 are considered to be in bankruptcy.

By applying Altman's model to predict the financial health of a company on a sample of companies, we obtained individual results for the years 2015-2019, which were then compared with the definition of a non-prosperous company according to Kliestik et al. (2019). Using Altman's model (AM) for calculating the financial health of the company, we obtained the following results:

*Table 3. Number of prosperous and non-prosperous enterprises (2017-2019) by AM*

| State of the business | 2019 | 2018 | 2017 |
|---|---|---|---|
| Prosperity/Non prosperity | 284/317 | 31/570 | 21/580 |

*Source: own calculations*

Subsequently, we compared these data with the determination according to Kliestik et al. (2019) for the years 2017-2019 and we also performed an analysis of error I. and error II.

Using Altman's model, we found that 53.41% of the prosperity and unprosperity in 2019 were accurately predicted by Altman's model. The value that results is also known as "Determination Success." In 321 businesses, Altman's model matched the data, but in 280 businesses it did not. Consequently, of the 321 businesses where the models agreed, 270 are doing well and 51 are either in danger of going out of business or are not doing well. We then conducted an analysis of the mistake I. and error II. type.

*Table 4. Comparison of the results of Altman's model with the results from table 3*

| ALTMAN 2019 | | PROSPERITY | NON-PROSPERITY |
|---|---|---|---|
| **MATCH** | 321 | 270 | 51 |
| **NON-MATCH** | 280 | - | |
| **TOTAL** | 601 | 321 | |
| **Determination success** | 53.4109 | | |
| **ALTMAN 2018** | | **PROSPERITY** | **BANKRUPTCY** |
| **MATCH** | 83 | 31 | 52 |
| **NON-MATCH** | 518 | - | |
| **TOTAL** | 601 | 83 | |
| **Determination success** | 13.8103 | | |
| **ALTMAN 2017** | | **PROSPERITY** | **BANKRUPTCY** |
| **MATCH** | 63 | 21 | 42 |
| **NON-MATCH** | 538 | - | |
| **TOTAL** | 601 | 63 | |
| **Determination success** | 10.4825 | | |

*Source: own calculations*

We can distinguish between mistake I. and error II. kind based on data. Businesses that were labelled as non-affluent by the model but are actually prosperous are referred to as Type I errors. 49.63% of successful businesses were misclassified as unsuccessful by the model during the year. Error II. in some ways discusses companies that are not actually rich but were given a prosperous classification by the model. Thus, up to 21.54% of non-prosperous firms were wrongly identified by the model as prosperous. Compliance in 2018 was 13.81%. Altman's methodology was accurate in 83 businesses and inaccurate in 518. Out of the 83 firms where the models aligned, 31 were designated as prosperous, while 52 were designated as non-prosperous. The type I mistake indicates that the model wrongly categorised 94.35% of truly wealthy firms as non-prosperous. Sort of based on mistake II., the model misclassified 0 enterprises. The success percentage of determination decreased to 10.48% in 2017. In 63 firms, Altman's model matched the data, whereas it did not in 538. A total of 63 matching firms were examined, and 21 were found to be lucrative, while 42 were not. The type I mistake indicates that the model misclassified 96.24% of truly wealthy firms as non-prosperous. Sort of based on mistake II., the model misclassified 0 enterprises. According to the Altman model, the total average success rate for businesses of all sizes in the economy sector known as SK NACE H (2017-2019) was 21.06%.

**Taffler's model**

Taffler's approach requires four indicators, which may be obtained from financial statements of businesses and, in our instance, the Amadeus database, to calculate the required Z-score. Based on the resulting Z-Score, Taffler, like Altman, establishes certain periods when the firm is in a particular financial state. The zone of prosperity, the grey zone, and the zone of bankruptcy are the same states of the company for Altman's model. The zones of prosperity and bankruptcy have once more been separated into two halves. The divide occurred according to Altman's concept (Cline et al., 2020). We calculated the distribution using the grey zone threshold values and identified its midpoint. With Taffler's approach, we will classify enterprises as flourishing if the resulting Z-score is more than 0.25 and as failing or showing a tendency toward bankruptcy if the Z-score is less than 0.25. We generated individual findings for the years 2017 to 2019 by using the Taffler model to forecast the financial health of a sample of organisations. These results were then contrasted with Kliestik et al., (2019):

*Table 5. Number of prosperous and non-prosperous enterprises (2017-2019) by TM*

| State of the business | 2019 | 2018 | 2017 |
|---|---|---|---|
| Prosperity/Non prosperity | 527/74 | 534/67 | 550/51 |

*Source: own calculations*

We compared the data once more with the estimation of prosperity made in Kliestik et al. (2019)'s book for the period 2015–19, and we also conducted an analysis of error I and error II.

*Table 6. Comparison of the results of Taffler's model with the results from Table 5*

| **TAFFLER 2019** | | **PROSPERITY** | **NON-PROSPERITY** |
|---|---|---|---|
| **MATCH** | 494 | 478 | 16 |
| **NON-MATCH** | 107 | - | |
| **TOTAL** | 601 | 494 | |
| **Determination success** | 82.1963 | | |
| **TAFFLER 2018** | | **PROSPERITY** | **BANKRUPTCY** |
| **MATCH** | 500 | 491 | 9 |
| **NON-MATCH** | 101 | - | |
| **TOTAL** | 601 | 500 | |
| **Determination success** | 83.1947 | | |
| **TAFFLER 2017** | | **PROSPERITY** | **BANKRUPTCY** |
| **MATCH** | 518 | 513 | 5 |
| **NON-MATCH** | 83 | - | |
| **TOTAL** | 601 | 518 | |
| **Determination success** | 86.1897 | | |

Source: own calculations

According to the previous table, Taffler's model matched in prosperity and non-prosperity at 82.20% in 2019. Taffler's model matched in 494 companies and did not match in 107 companies. Subsequently, for the 494 enterprises that matched, the division was valid: 478 prosperous enterprises and 16 non-prosperous enterprises. Based on data we can identify error I. and error II. Type I error refers to businesses that are actually prosperous, but were classified as non-prosperous by the model. The model incorrectly classified 10.82% of prosperous enterprises as non-prosperous in 2019 among such enterprises.

Error II. of talks about businesses that are not really prosperous, but were classified as prosperous by the model. Up to 75.38% of non-prosperous firms were wrongly identified as prosperous by the model in this fashion. The success rate was greater during the prior year, 2018, at 83.19%.

Taffler's methodology was accurate in 500 firms and inaccurate in 101. Following that, the distribution of the 500 firms that concur in determining financial health is as follows: 491 successful enterprises and 9 non-prosperous enterprises. The type I mistake indicates that the model misclassified 10.56% of extremely successful businesses as non-prosperous. The model misclassified 82.69% of non-wealthy enterprises that are actually prosperous based on mistake

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II. In 2017, 86.19% of people who were determined succeeded. Taffler's model matched in 518 businesses while failing to match in 83. 513 successful and 5 non-prosperous firms were identified out of 518 matched enterprises. The algorithm misclassified 8.23% of extremely successful businesses as non-prosperous, according to the type I mistake. The model misclassified 88.10% of non-wealthy enterprises that are actually prosperous based on mistake II. Analysis of errors I and II sort of hinted to a significant number of successfully operating firms that were incorrectly classified, which may lead to improper actions being made or a change in a successfully operating system in the business. For businesses of various sizes in the economic sector known as SK NACE H, the Taffler model's overall average success rate for the years 2015 to 2019 is 85.92%.

**Prediction model based on discriminant analysis in the economic conditions of the Slovak Republic**

For the circumstances of the Slovak economy, a prediction model was also created. The methodology employs 16 variables to determine how well the organisation is doing financially. The geography and size of the firm are among the factors taken into account when calculating the Z-score (y) (Podhorska et al., 2020). The band or zone that the firm belongs to is again determined by the resulting Z-score(s). The same distribution holds true for the discriminant analysis-based prediction model for businesses that operate inside the borders of the Slovak Republic. If the Z-score (y) is larger than 0, the business is said to be unprosperous. If it is less than 0, the business is seen to be successful. 836 businesses were included in the sample. The total number of firms was lowered to 601 after data cleansing.

We acquired the following information on the success of businesses using a generic prediction model for firms in the conditions of the Slovak economy in the years 2017–2019.

*Table 7. The number of prosperous and non-prosperous enterprises according to the prediction model based on discriminant analysis for enterprises operating in the Slovak Republic*

| State of the business | 2019 | 2018 | 2017 |
|---|---|---|---|
| Prosperity/Non prosperity | 11/490 | 102/499 | 96/505 |

*Source: own calculations*

We again compared the data once more with the estimation of prosperity made in Kliestik et al. (2019)'s book for the period 2015–2019, and we also conducted an analysis of error I and error II. Table 8 shows that the discriminant analysis-based prediction model for businesses situated in the Slovak Republic correctly predicted both prosperity and unprosperity by 29.28% in 2019. The discriminant analysis-based prediction model for businesses with operations in the Slovak Republic matched 176 businesses while failing to match 425 others. The distribution was then accurate for the 176 matching businesses: 111 successful businesses and 65 unsuccessful businesses. We distinguish between mistake I. and error II. kind throughout the analysis. According to a type I inaccuracy, the model for 2019 wrongly categorised 79.25% of successful enterprises as non-prosperous. Error II. in some ways discusses companies that are not actually rich but were given a prosperous classification by the model. None of the 0 percent of non-prosperous firms that the model wrongly labelled as prosperous.

*Table 8. Comparison of results using a prediction model based on discriminant analysis for companies operating in the Slovak Republic with results according to Table 7*

| ENTERPRISES IN SK 2019 | | PROSPERITY | NON-PROSPERITY |
|---|---|---|---|
| **MATCH** | 176 | 111 | 65 |
| **NON-MATCH** | 425 | - | |

| | | | |
|---|---|---|---|
| **TOTAL** | 601 | 176 | |
| **Determination success** | 29.28453 | | |
| **ENTERPRISES IN SK 2018** | | **PROSPERITY** | **BANKRUPTCY** |
| **MATCH** | 154 | 102 | 52 |
| **NON-MATCH** | 447 | - | |
| **TOTAL** | 601 | 154 | |
| **Determination success** | 25.62396 | | |
| **ENTERPRISES IN SK 2017** | | **PROSPERITY** | **BANKRUPTCY** |
| **MATCH** | 132 | 93 | 39 |
| **NON-MATCH** | 469 | - | |
| **TOTAL** | 601 | 132 | |
| **Determination success** | 21.96339 | | |

*Source: own calculations*

The success rate for the prior year, 2018, was lower (25.62%). The prediction model for businesses operating in the territory based on discriminant analysis matched 154 businesses and did not match 447 businesses. The distribution is then used for the 154 businesses that concur in determining financial health: 102 successful businesses and 52 unsuccessful businesses. The type I mistake indicates that the model misclassified 81.42% of truly wealthy firms as non-prosperous. Based on mistake II, the model misclassified all of the unsuccessful enterprises as successful. The success rate of willpower fell by 21.96% in 2017. The discriminant analysis-based prediction model for businesses with operations in the Slovak Republic matched in 132 businesses and did not match in 469 businesses. There were 132 matching firms, 93 of which were lucrative, and 39 of which were not. The type I mistake indicates that the model misclassified 83.45% of truly wealthy businesses as non-prosperous. Based on mistake II, a model misclassified 7.14 percent of supposedly unsuccessful businesses as successful ones.

**Prediction model based on discriminant analysis in the economic conditions of the Slovak Republic in sector SK NACE H**

Only 6.4% of natural people who are entrepreneurs in the Slovak Republic are interested in conducting business in the SK NACE H sector, according to data from the Statistical Office of the Slovak Republic and a 2018 poll. A forecasting model created for the circumstances of the Slovak economy for businesses included in the SK NACE H sector of the economy (Kovacova et al., 2018,). The company's grade is determined by the model using 14 indicators and factors. The Z-score computation takes into account factors including the company's size and the region in which it operates. Once more, the resulting Z-score establishes which band or zone the firm belongs to. The projection model for businesses based in the Slovak Republic in the SK NACE H economy part follows the same distribution as in earlier chapters. We thus consider the firm prosperous if the Z-score is smaller than 0. If the Z-score is higher than 0, the company is said to be unprofitable (Zvarikova et al., 2017).

836 businesses were included in the overall sample. The total number of firms was lowered to 601 after data cleansing. The following information about their success was gathered using the prediction model for firms in the circumstances of the Slovak economy in the economics section SK NACE H in the years 2017–2019. We discovered that the following distribution of the status of enterprises applies for the period 2015–2019 by applying the prediction model for businesses in the circumstances of the Slovak economy in the economics section of SK NACE H.

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*Table 9. The number of prosperous and non-prosperous enterprises according to the prediction model based on discriminant analysis for enterprises operating on the territory of the Slovak Republic in the sector SK NACE H*

| State of the business | 2019 | 2018 | 2017 |
|---|---|---|---|
| Prosperity/Non prosperity | 403/198 | 59/542 | 33/566 |

*Source: own calculations*

Following a comparison with Kliestik et al. (2019)'s definition of prosperity for the period 2015–2019, we conducted an analysis of error I. and error II. type.

*Table 10. Comparison of results using a prediction model based on discriminant analysis for companies operating on the territory of the Slovak Republic in the SK NACE H sector with the results according to table 9*

| **SECTOR H 2019** | | **PROSPERITY** | **NON-PROSPERITY** |
|---|---|---|---|
| **MATCH** | 372 | 355 | 17 |
| **NON-MATCH** | 229 | - | |
| **TOTAL** | 601 | 372 | |
| **Determination success** | 61.8968 | | |
| **SECTOR H 2018** | | **PROSPERITY** | **BANKRUPTCY** |
| **MATCH** | 63 | 35 | 28 |
| **NON-MATCH** | 538 | - | |
| **TOTAL** | 601 | 63 | |
| **Determination success** | 10.4825 | | |
| **SECTOR H 2017** | | **PROSPERITY** | **BANKRUPTCY** |
| **MATCH** | 45 | 19 | 26 |
| **NON-MATCH** | 556 | - | |
| **TOTAL** | 601 | 45 | |
| **Determination success** | 7.48752 | | |

*Source: own calculations*

We found that, based on the prior table, the discriminant analysis-based prediction model correctly predicted 61.90% of 2019 prosperity and unprosperity for businesses operating on Slovak Republic territory in the SK NACE H sector. The discriminant analysis-based prediction model for businesses engaged in the SK NACE H sector in the Slovak Republic matched in 372 firms while failing to match in 229 firms. Consequently, 355 of the 372 businesses where the models agreed on performance are successful, whereas 17 are either not prospering or are in danger of failing. We also pinpoint error number 1. and II. kind. According to a type I inaccuracy, the model for 2019 wrongly categorised 33.77% of successful firms as non-prosperous. Error II. in some ways discusses companies that are not actually rich but were given a prosperous classification by the model. Thus, 74.24% of non-successful firms were misclassified by the model; they were thought to be prosperous.

Compliance in 2018 was 10.48%. The discriminant analysis-based prediction model for businesses engaged in the SK NACE H sector in the Slovak Republic matched 63 businesses while failing to match 538. Out of the 63 businesses where the models matched, 35 were designated as prosperous, while 28 were designated as non-prosperous. The type I mistake shows that the model misclassified 93.68% of extremely successful firms as non-prosperous. Based on mistake II, a model misclassified 40.43% of firms that should have been prosperous as non-prosperous. The success percentage of determination decreased to 7.48% in 2017. The discriminant analysis-based prediction model for businesses engaged in the SK NACE H sector in the Slovak Republic matched 45 businesses while failing to match 556. A total of 45 matching firms were examined, and 19 were found to be lucrative, while 26 were not. The model incorrectly identified 96.61% of truly wealthy firms as non-prosperous, according to the type I mistake. A model misclassified 36.59% of non-successful enterprises that are really prosperous based on mistake II. For businesses in the economic sector with the designation SK NACE H, the overall average success rate for the years 2015 through 2019 using the prediction model for businesses in the Slovak Republic's economic circumstances is 18.26%.

## 4. Results

After thoroughly examining a sample of 601 businesses from the SK NACE H industry and Slovakia's economic climate from 2015 to 2019, we also chose to compare the models that had the greatest classification skills using ROC curves. We suggest the Taffler model, a prediction model based on discriminant analysis for businesses operating in Slovakia's SK NACE H sector, a prediction model based on discriminant analysis for businesses operating in Slovakia's economic conditions, and a prediction model based on discriminant analysis for businesses operating in Slovakia's SK NACE H industries, among other models from our research. The 1-specificity and sensitivity connection is described and shown via the ROC curve. We are discussing the connection between real and fake positive. We generate the ROC curve using the specificity and sensitivity values from the computations. After creating the curve, we keep an eye on the AUC, or area under the curve. The following values determine the categorization ability:

*Table 11. Classification of AUC based on the resulting values*

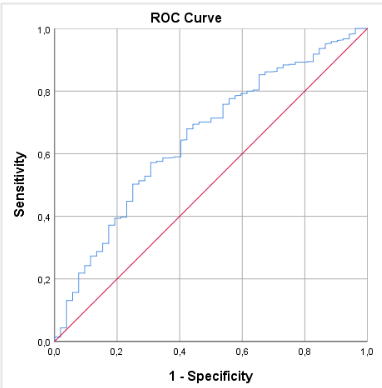
| | |
|---|---|
| 0.5-0.75 | Acceptable classification ability |
| 0.75-0.92 | Good classification ability |
| 0.92-0.97 | Very good classification ability |
| 0.97-1 | Perfect classification ability |

*Source: own calculations*

**ROC for Taffler's model**

In order to get the best classification accuracy when contrasting the outcomes of the financial health of companies with the financial health of companies, we created the ROC curve for the Taffler model.

*Figure 1. ROC curve - Taffler 2019*



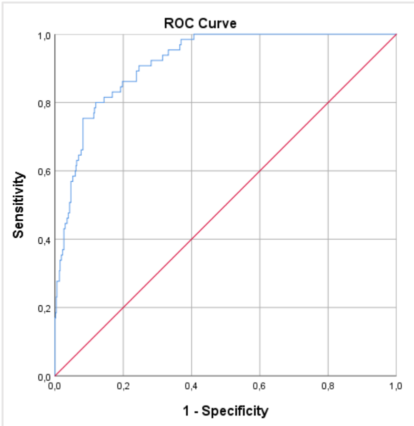

*Source: own calculations*

We assess the produced outcomes based on the AUC (Area Under Curvature). In 2019, we are referring to a value of 0.629 for Taffler's model. This value climbed to a level of 0.652 in 2018. The value stayed same in 2017 at 0.652. However, the value increased once again in 2016 to reach 0.720. The number decreased to 0.642 during the most recent year, 2015. We can state that in our instance, the Taffler model has an appropriate classification ability in each assessment year based on the previous results.

**ROC for a model based on discriminant analysis in the economic conditions of Slovakia**

We conducted an investigation using ROC curves with the following findings to confirm the classification capability of the prediction model based on discriminant analysis in the economic circumstances of Slovakia:

*Figure 2. ROC curve – Model based on discriminant analysis in the economic conditions of Slovakia 2019*




*Source: own calculations*

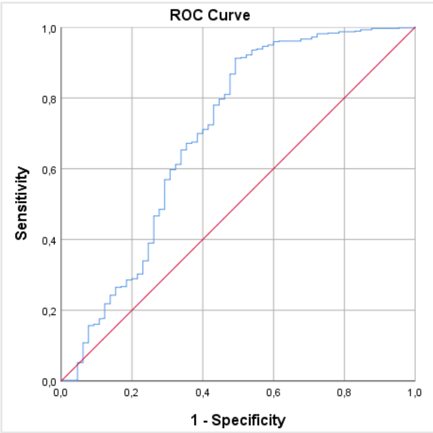
We describe the link between false and true positive using the ROC curve. We re-evaluate the findings obtained based on the AUC (Area Under Curvature). We are discussing a value of 0.918 for the prediction model for enterprises in the Slovak Republic in 2019. 2018 saw a decrease in this metric, which fell to 0.875. The rating decreased once again in 2017 to a level of 0.785. However, the value increased once again in 2016 to reach a level of 0.896. The number decreased to 0.786 during the most recent year, 2015. In our situation, the prediction model for the firms of the Slovak Republic has a strong classification ability in each assessment year, even if in 2019 the value almost touched a very excellent classification ability. This is based on the findings from the previous analysis.

**ROC for a model based on discriminant analysis for companies operating in Slovakia in the SK NACE H sector**

In the area of error calculations II. type, a model that has produced great results. One of the explanations why why we used ROC curves in the examination of this model. We conducted an investigation using ROC curves with the following findings to confirm the classification capability of the prediction model based on discriminant analysis in the Slovakia. (Figure 3).

The connection between false and correct positive is expressed using the ROC curve. We re-evaluate the outcomes on the basis of AUC (Area Under Curvature). We are discussing a value of 0.699 for the forecast model for Slovak Republic businesses in 2019. 2018 saw a rise in this number, which reached 0.797. In 2017, the value increased once again to reach 0.851. In 2016, the rating decreased slightly to 0.813. The rating increased to 0.827 for the previous year, 2015. Our case's prediction model for Slovak Republic businesses in the economics part of SK NACE H has an adequate capacity to classify entities in 2019 and an excellent ability to classify entities in the years 2017–2018, according to the previous findings.

*Figure 3. ROC curve – Model based on discriminant analysis for companies operating on the territory of the Slovak Republic in the sector SK NACE H 2019*




*Source: own calculations*

## 5. Discussion

We made the decision to further examine the data using sensitivity and specificity in order to have a more thorough potential of creating models and their verification in the chosen sector. The ratio of actually, truly positive cases to all positive cases is expressed by the term "sensitivity." In our instance, it is a proportion of really successful companies. The ratio of actually, truly negative cases to all negative cases is expressed by specificity. In our situation, it represents the percentage of truly unsuccessful firms (Table 12).

We choose to define the best models as those that demonstrate a high percentage of specificity, considering the purpose of the work and the fundamentals of bankruptcy models. The ability of the organization to quickly respond to the possibly unfavorable trend it is going towards is crucial. We rank the prediction model for small businesses, the prediction model for enterprises working in the SK NACE H sector in Slovakia, and the Altman model as the three top models from this page based on the analyses we conducted. The models in question attained excellent specificity scores, with an average of over 90%.

*Table 12. Classification of results based on selected parameters*

| Model | Year | Correct determ. (%) | Error I. (%) | Error II. (%) | Sensitivity (%) | Specificity (%) | AUC |
|---|---|---|---|---|---|---|---|
| | 2015 | 18.80 | 85.89 | 2.94 | 14.11 | 97.06 | |
| | 2016 | 8.82 | 96.31 | 0 | 3.69 | 100.00 | |
| **Altman's model** | 2017 | 10.48 | 96.24 | 0 | 3.76 | 100.00 | x |
| | 2018 | 13.81 | 94.35 | 0 | 5.65 | 100.00 | |
| | 2019 | 53.41 | 49.63 | 21.54 | 50.37 | 78.46 | |
| | 2015 | 89.35 | 7.23 | 67.65 | 92.77 | 32.35 | 0.642 |
| **Taffler's model** | 2016 | 88.69 | 7.56 | 78.13 | 92.44 | 21.88 | 0.720 |
| | 2017 | 86.19 | 8.23 | 88.10 | 91.77 | 11.90 | 0.652 |
| | 2018 | 83.19 | 10.56 | 82.69 | 89.44 | 17.31 | 0.652 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2019 | 82.20 | 10.82 | 75.38 | 89.18 | 24.62 | 0.629 |
| **Discrimination model for Slovakia** | 2015 | 18.64 | 85.87 | 5.88 | 14.08 | 94.12 | 0.786 |
| | 2016 | 19.63 | 84.86 | 0 | 15.14 | 100.00 | 0.896 |
| | 2017 | 21.96 | 83.45 | 7.14 | 16.61 | 92.86 | 0.785 |
| | 2018 | 25.62 | 81.42 | 0 | 18.55 | 100.00 | 0.875 |
| | 2019 | 29.28 | 79.25 | 0 | 20.79 | 100.00 | 0.918 |
| **Discrimination model for SR in SK NACE H** | 2015 | 5.16 | 98.06 | 20 | 1.94 | 80.00 | x |
| | 2016 | 6.32 | 96.64 | 40.63 | 3.35 | 55.88 | |
| | 2017 | 7.48 | 96.61 | 36.59 | 3.41 | 57.78 | |
| | 2018 | 10.48 | 93.68 | 40.43 | 6.34 | 53.85 | |
| | 2019 | 61.90 | 33.77 | 74.24 | 66.36 | 26.15 | |

*Source: own calculations*

The Taffler model had the highest determination accuracy, according to a comparison of the findings of an investigation employing prediction models on a sample of 601 businesses in the SK NACE H sector of the economy (transport and storage). Taffler's model properly predicted an average of 85.92% of firms for the evaluated years 2017–2019. General indicators including foreign resources, current assets, financial assets, operational costs, profit before tax, and short-term obligations are all considered in the computation. However, we would like to draw attention to the substantial number of mistakes classified as type II. faults. On average, Taffler's approach misclassified 78.39% of non-prosperous enterprises as prosperous. For businesses functioning in the SK NACE H sector of the economy, a mistake of this nature and the formulation of a plan based on a forecast in accordance with Taffler's model can have a detrimental or even deadly influence on the operation of the organization. The examination of ROC curves, where the model was rated with the poorest, i.e., acceptable, classification performance, also draws attention to this issue. The model has relatively low specificity values (21.61% on average) but high sensitivity values (91.12% on average) when sensitivity and specificity analysis was used.

In the circumstances of Slovakia in the SK NACE H sector, the results of the Altman model and the model based on discriminant analysis were unexpected. The determination had a comparatively low rate of success. In the SK NACE H sector, the model based on discriminant analysis in Slovak circumstances averaged 18.26%, compared to 21.06% for Altman's model. While Altman's model has a low mistake rate II. type and thus classified a tiny number of firms as affluent even if they are not, we consider the low success rate of the classification and the fact that it was created for the US market. This model should just serve as information for businesses engaged in the transportation and storage of goods, and it shouldn't serve as the foundation for elaborate planning or business strategies. We conducted an investigation using ROC curves, which revealed a good to acceptable classification ability, since the model based on discriminant analysis in Slovakia's SK NACE H sector attained a low explanatory power. The discriminant analysis-based prediction model under Slovak settings has an average success rate of 23.02%. Of all the assessed models, it exhibits the least amount of error II. of the sort. We can thus assert that there is a good chance the model has accurately identified companies that are struggling so that we can proceed to the phase of conserving money and preventing a potential negative effect. A high categorization ability that was evaluated as good to very good was also attained.

We arrived at contrasting conclusions after applying a selection of international and local prediction models. Every single outcome was unique, and over the studied years of 2015–2019, not a single model accurately predicted the true state of the sector (only the years 2017-2019 were used for illustrations). But although some of these models were remarkably accurate, others were completely off the mark. There are many different variables, predictors, and weights used in models for predicting a company's financial health. Every model is unique. However, we may discuss altered forms, such as those that exist between the Taffler and Altman models.

We looked for a model with high values of determination success, high values of AUV, high percentage rates of sensitivity and specificity, and low values of I. and II. kind mistakes among the acquired results of the analyses. Based on the outcomes, we advise businesses engaged in the SK NACE H economic sector (transport and storage) to utilize models developed specifically for the features of the Slovak economy. We are referring to the models that Kliestik et al. (2019) published. These models were created keeping in mind Slovakia's economic situation. Liabilities and assets are the main focus of the models since they are utilized to calculate ratios (Kliestik et al., 2020). Indicators like net income to equity, current obligations to total assets, long-term liabilities to total assets, and working capital to total assets are particularly important. Since they represent the actual status of the firm, businesses should concentrate on models that employ the aforementioned ratios. They attained high specificity levels, which represent the percentage of accurately recognized unsuccessful enterprises. For the business, knowledge of this condition is crucial. Taffler's model had a high success rate of determination, but the ROC curve study also showed that it was not appropriate for use with SK NACE H firms.

The investigation of sensitivity and specificity revealed that while Altman's model had excellent specificity values, it had low sensitivity values. Similar to Taffler's model, which was developed for the US market, we advise against utilizing Altman's model until absolutely necessary and when the firm lacks the real-time access to sufficient material to conduct a more thorough study of its financial health.

## 6. Conclusions

The models that were most successful in predicting the financial health of the firm and models whose success rates we didn't like are discussed in the preceding section of the study. For businesses operating in Slovakia in the SK NACE H sector, we conducted the study on the Taffler's model, model, prediction model based on discriminant analysis, and model based on discriminant analysis. The classification abilities of the models assessed using ROC curves ranged from fair to perfect. With an average grade of 0.852, the discriminant analysis-based prediction model had the best classification performance. A model using discriminant analysis for businesses operating in Slovakia's SK NACE H sector, with an average value of 0.8, was then used. The Taffler model, with an average value of 0.66, is the lowest model among those assessed using ROC curves, while the model for big firms came in last with an average value of 0.77. The outcomes of the analyses were then included into a table that categorizes the outcomes based on certain criteria, including the success of assessing the company's financial health, error I and II. species, and AUV (the result of the analysis using the ROC curve).

Taffler earned the highest values in the field of determination success, but with a high error II. species and poor categorization skills. The model based on discriminant analysis produced the poorest results for businesses operating in Slovakia in the SK NACE H sector in the area of determination success, but we were able to prove this with the use of ROC curves. The fact that our sample is made up of few businesses and businesses with total assets under €500,000 may have an impact on the low determination success. We consider a prediction model based on discriminant analysis, which achieved low percentage results in the field of determination success, but when looking at error I. and II. of sorts, we claim that the model incorrectly classified 82.97% of prosperous businesses as non-prosperous. This is from the point of view of the best, even perfect classification ability. In this instance, the firm may examine its present financial status in further detail and determine how well it corresponds to reality when compared to businesses that are on the verge of bankruptcy yet were evaluated as successful by Taffler's model.

It would be appropriate to use the models developed in the article Kliestik et al. (2019) and primarily concentrate on models that use variables like return on equity, the ratio of working capital to total assets, and current liabilities/total assets to predict the financial health of a company in similar analyses for the SK NACE H sector (transport and storage). Despite the fact that foreign models like Altman's and Taffler's can be used to anticipate a company's financial health, we advise financial managers for Slovak businesses to just use the findings as information. The study contains a number of drawbacks, despite the analysis's thorough objective. It should be mentioned that this study was carried out in only one nation. It must be acknowledged, nonetheless, that the socioeconomic environment, culture, and particularly the legal environment are crucial in this area of economics, therefore this flaw may also be seen as meaningful and advantageous. The analysis and comparison of these models in the V4 nations in Central Europe is our next task.

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