# FORECASTING OF FINANCIAL HEALTH IN TRANSPORTATION AND STORAGE SECTOR

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***Abstract***

The paper's aim is the forecasting of corporate financial health. It is focused on the specific sector of economic activity – Transportation and Storage in the Czech Republic which is labelled as CZ-NACE H. There could be used various tools for forecasting. In the case of finance, models predicting financial distress are widely used for fulfilling this purpose. They provide an answer if the company is exposed to the risk of bankruptcy or if its financial health reaches a satisfying level. In a period of economic expansion, models should classify most businesses as healthy with a very low risk of bankruptcy. There is one obstacle because no universal model exists. Some models provide better results for manufacturing companies, others for services, emerging markets or transition economies. Transportation and Storage Sector has its own specifics from different points of view and financial perspective is no exception. Although the main aim of the paper is forecasting of corporate financial health, another goal is detecting the prediction model or models best fulfilling the aforementioned aim.

**Key words:** models predicting financial distress, prediction formulas, Czech Republic

## 1. INTRODUCTION

Forecasting and predicting of the future state of the world is the foundation of business and entrepreneurship. Companies try to predict consumer demand, development of prices or costs but also the future development of their business relations. No manager wants to cooperate with partners who are at risk of closure or bankruptcy. Prediction of bankruptcy became a serious research question back in 1960's (Altman, 1968 or Beaver, 1966). Efforts ended with the creation of models predicting financial distress also called bankruptcy models. These models usually use corporate financial data for their prediction because the current state influences the future. These approaches provide their users a quick and inexpensive prediction about the future of the related company whose development can affect one´s own business.

There have been created thousands models fulfilling purpose discussed aforementioned since 1960's. Many of them created a know-how of their users and therefore were never published. Some models lost their prediction ability during years and therefore new models have been created. The debate about the models predicting financial distress always increases due to serious political or economic changes. The last global economic crisis was no exception. In the Czech Republic papers by Klečka & Scholleová (2010), Pitrová (2011), Karas & Režňáková (2013), Machek (2014) or Čámská (2015) addressed this issue. These papers generally tested the explanatory power of the already existing models and discussed the necessity of new models. This paper continuous these efforts. For its analysis, it uses models predicting financial distress which had high explanatory power tested by Čámská (2016). The tested models will be introduced in the following chapter. These traditional approaches are mainly used for an evaluation of the companies belonging to manufacturing. But let's ask if these models can be used for the companies operating in Transportation and Storage in the Czech Republic which is labelled as CZ-NACE H.

The models predicting financial distress can have a variety of users. First, managers might use them for the evaluation of their own company. It shows a time development and improvement or worsening of the financial situation. It must be noted that this is not the real models' purpose. The managers mostly evaluate related companies as suppliers, customers or even competitors. It enables them to mitigate business risks. Banks and other financial institutions usually create their own models and tools predicting financial distress or potential default. Their goal is to assess the financial situation when they decide about credit providing and conditions of loan contracts. Previous years especially in the new EU member countries have shown the importance of this issue in an area of subsidies and other kinds of support. The financial situation of each applicant is evaluated by various models.

There does not exist any universal model, hence the company's specifics (such as maturity, ownership structure, industry, share of tangible assets etc.) influence the results. This paper focuses on one company's specific and that is its belonging to a particular industry branch.

## 2. TESTED MODELS

This chapter will present the models which will be tested. As was previously mentioned, these models have already proven their accuracy in Čámská (2016). The analysed models arise from different political, economic and geographical environments. A data sample will work with the Czech data and therefore there is a significant focus on the Czech predicting approaches. The Czech models are accompanied by the models from other European countries which were called transition economies in 1990's. The whole group is completed by the world-famous models by Altman (1993), Taffler (1982) fully published in Agarwal & Taffler (2007), Bonita model (in the German original Bonitätsanalyse, Wöber and Siebenlist, 2009) or Kralicek model (Kralicek, 2007) which are still very popular in the environment of the Czech Republic.

The basis of Czech models is concentrated around the IN index family, specifically IN01 (Neumaierová and Neumaier, 2002) and IN05 (Neumaierová and Neumaier, 2005). Other Czech approaches which will be verified are Grünwald Bonita Index (Grünwald, 2001) and Balance Analysis System by Rudolf Doucha

(Doucha, 1996). The models arising from the transition economies are represented by the Polish models Prusak 1, Prusak 2, PAN-E, PAN-F, PAN-G, D2 and D3 (Kisielinska and Waszkowski, 2010), the Hungarian model Hajdu & Virág (2011) and the Baltic approaches Šorins/Voronova (Jansone, Nespors and Voronova, 2010), Merkevicius (Merkevicius et al, 2006) and R model (Davidova, 1999). This paper does not list formulas of each tested model because the extension of the paper would be too long. Interested readers can find the formulas in the relevant mentioned literature.

## 3. METHODOLOGY AND OBJECTIVES

This chapter is dedicated to a used research methodology and solved research objectives. The chapter is divided into several subparts. The part Paper's objectives defines the research questions solved in the paper. The part Research methods explains the measures used for the verification of models' accuracy. The part Selected area of industrial activity shows the economic sector which is in the centre of the verification and it poses its importance and specificity as well as papers connected with the special issue. At the end, attention is paid to the data sample and defines the analyzed companies.

### 3.1. Paper's objectives

The paper verifies the accuracy of models predicting financial distress in the specific sector of economy. The previous chapter defined the models which had higher accuracy in the area of manufacturing and construction. The research should provide an answer if these models are also suitable for the area of logistics or if there is a need of special predicting tools. This is the first research question. The second one is to detect the model/s with the highest possible accuracy. The models with the best reliability should be recommended for a use in practise and contrary the use of the models with low explanatory power should be restricted. It could especially reduce the universality for subsidiary programs financed and co-financed by the European Union and national or local governments.

### 3.2. Research methods

The models' reliability and accuracy can be expressed by several metrics such as Cumulative Accuracy Profiles (CAPs); Accuracy Ratios (ARs); Conditional Information Entropy Ratio (CIER); Mutual Information Entropy (MIE) described by Sobehart et al. (2000). These tools seem to be too complicated in connection with the published models predicting financial distress which are popular and widely used because of their simplicity and user-friendliness. It must be noted that models are generally only a simplification of the reality and therefore they work on probabilistic roots (eg. Altman, 1968 or Farooq ae al., 2018) and not all companies can be classified correctly. At the beginning, creation and verification in almost all papers are based on measures such as Type I Error and Type II Error. These measures show an incorrect classification of the tested companies. Type I Error is connected with the incorrect classification in case of the defaulted companies and Type II Error is for the group of the non-defaulted companies. The following table offers a better explanation by showing the division according to classified categories.

**Table 1.** Type I Error and Type II Error

| | | Estimated | |
|---|---|---|---|
| | | Non-default | Default |
| Observed | Non-default | True | False Alarm (Type II Error) |
| | Default | Miss (Type I Error) | True |

Source: Fernandes (2005)

If numbers of Type I Error and Type II Error are summed up for an analysed sample, one obtains the absolute value of both kinds of errors. Higher value means lower accuracy because the tested model does not provide relevant answers for further decision making. The gained absolute values are highly dependent on a sample size and therefore it is more convenient to use the relative values instead of the absolute ones. Type I Error as a ratio is constructed as all incorrect classified defaulted companies divided by all defaulted companies. Type II Error as a ratio is constructed analogically for the non-defaulted companies. On one hand it is required to keep the error rate as low as possible and on the other hand to keep the reliability as high as possible. The reliability can be expressed as a ratio as well which has in a numerator the number of all correctly classified (non-)defaulted companies and in a denominator the number of all (non-)defaulted companies. In many cases there is not valid that error ratio plus reliability ratio are equal to 1. It is caused by the model construction itself. Many models do not work only with two groups: healthy and unhealthy but they also use a grey zone which is situated between the two aforementioned extremes. Another reason is that the used model is not able to evaluate the corporate financial situation because of the data whose selected items are equal to zero. This will be discussed in more detail in a chapter dedicated to results. The used research methods have to work with the error rates as well as with the reliability rates. For a user it is crucial to get the lowest wrong classification and the highest correct one.

It is difficult to define the sufficient level of the models' reliability. It is certain that the reliability should exceed 50% probability (otherwise the coin flipping provides the same result) and the error rate should be lower than 50%. The model is generally accepted if its error rate does not exceed 20%. Data samples should be evaluated separately. It means that the results for the defaulted entities should be first evaluated without the non-defaulted entities. Some models can be too strict and others too moderate. The best suitable models for defaulted and non-defaulted entities are compared in the following step. The most accurate models are those, whose tools provide reliable results for the defaulted as non-defaulted companies.

### 3.3. Selected area of industrial activity

Models predicting financial distress are usually verified on one or more entrepreneurial sectors. It has to be taken into account that there are differences among sectors in the performance, indebtedness, used property etc. The verification is usually performed on the companies belonging to manufacturing because they have a common goal to produce products for customers and many other common features. They created the backbone of the economy although the centre has shifted to services. It can be applied to the manufacturing industry as a whole group as in the case of Karas & Režňáková (2013) or Machek (2014) or on individual industry sectors belonging to manufacturing as Klečka & Scholleová (2010) or Čámská (2015 or 2016). Other sectors than manufacturing are analysed rarely because the most of models predicting financial distress were mainly constructed for the verification of the companies operating in manufacturing. The last global economic crisis introduced a need of the verification also in other entrepreneurial sectors. One example can be presented by logistics including transport and storage which are typical cycle-sensitive industries (Maripuu & Maennasoo, 2014). Due to cyclical sensitivity the economic crisis affects this sector extremely quickly and it spreads further. There can be found papers verifying accuracy of the models predicting financial distress in the area of logistics. Typically it is focused on specific countries whose economy is heavily dependent on transport and connected activities. Let's mention Lithuanian papers Kanapickiene & Spicas (2016) or Marcinkevicius & Kanapickiene (2014), Polish papers Juszczyk (2010) or Brozyna et al. (2016) focused on Poland and Slovakia. There are not such specific papers for the Czech Republic which verify the accuracy of models predicting financial distress in the area of logistics. There can be found papers focusing generally on the financial situations of the companies belonging to logistics in the Czech Republic as Hyršlová et al. (2018) or Telecký (2015).

### 3.4. Data sample

Models' verification significantly depends on a used data sample and therefore it has to be explained which business entities have been included in a data sample. The data sample consists of two groups. First group has to be represented by unhealthy companies and second group has to contain healthy companies for fulfilling the purpose of the models predicting financial distress. The definition of the healthy and unhealthy companies is too general and it has to be specified for a companies' selection.

The situation is simpler in the case of the unhealthy companies because these companies have to be ailing with serious consequences on their long-term existence. There is not a uniform definition of unhealthy or defaulted companies according to the literature review. Depending on publicly available data it can be used the definition provided by Act No. 186/2006 Coll., Bankruptcy and Settlement (the Insolvency Act) in the Czech Republic. This paper considers the defaulted companies to be insolvent. A declared insolvency proposal is a start of an insolvency proceeding. From the corporate database Albertina there have been extracted the companies with the insolvency proposals declared in the time period 2014-2018 plus first months of the year 2019. It is the post-crisis period of stable conditions in the Czech economy (Volejníková & Řezníček, 2016). It has an advantage that the results are not affected by exceptional economic conditions.

The second limitation is availability of financial statements which are crucial for the verification of the models predicting financial distress. It is widely accepted that financial problems have been already occurring for several years before bankruptcy. For this statement it can be noted Beaver (1966), Altman (1968) and many others. The data sample works with the financial statements constructed one or two years before the insolvency proposal. The chosen time of the financial data is important because older data did not have to contain any signs of coming problems yet. On the other hand the financial statements drawn up after the insolvency proposal are too much affected by the corporate crisis and they cannot be used for the prediction any more. The final data sample consists of 30 companies operating in CZ-NACE H whose financial statements constructed one or two years before the insolvency proposal are publicly available. The data sample does not seem wide but it is exhaustive according to the number of insolvency proceedings at the analysed time and the unavailability of financial statements. Although publishing of financial statements is required by the law in the Czech Republic it is not very much respected and especially in the case of the ailing companies (Bokšová & Randáková, 2013).

It can be assumed that the group of healthy companies is willing to publish their financial statements more in comparison with the insolvent ones. On the other hand there does not exist any guideline how to select companies which are supposed to be classified as healthy. The right verification should not be based on the general sample containing all companies registered and operating in the given industry but it should be based on the sample containing really healthy entities. One solution leads through a positive economic value added which were already used in papers Čámská (2015 or 2016). The positive economic value added can be identified as an increase of invested capital which is considered to be the most important enterprise goal (Synek & Kislingerová, 2010 or Tirole, 2006). The healthy group is defined as the companies creating the positive value added in the year 2017 for the purpose of this paper. Although it is the year 2019 there have not been published financial statements for the year 2018 in the case of most companies. The year 2017 represents the last possible one for which almost all willing companies published already their financial statements. The positive value added is determined as ROE (net income divided by equity) exceeding the minimal profitability requirement for owners published by Czech Ministry of Industry and Trade (MPO, 2018). It works with a disadvantage that the value added is based on the accounting data instead of the market data (Jordan at al., 2011). It must be noted that the market data are rarely available in the Czech Republic because of the ineffective capital market and therefore this indicator seems as the best one for measuring the main corporate goal and for solving a choice of the healthy companies.

The extraction of the data sample was performed in several steps as shown in the following table. First there were detected the companies operating in CZ-NACE H whose financial statements are available for the year 2017 and whose entrepreneurial activity is not connected with any insolvency proposal (it is crucial for the unhealthy companies). After first extraction there were 2352 statistical units with different level of the financial health and performance. The second step follows the positive economic value added but this step is divided in two sub-parts because of the paradox ROE (Strouhal et al., 2018). The positive value of the indicator ROE can be even gained for the negative net income in the case of negative equity (caused by cumulated losses in the previous periods). If net income is negative the company does not create the positive economic value added at all. The first sub-part searches the companies with the positive value of the indicator ROA (based on the ratio income to assets which have to be positive) and there were detected 1697 statistical items. The last sub-part follows ROE exceeding the minimal profitability requirement for owners. The Ministry of Industry and Trade (MPO, 2018) published the minimal profitability requirement for owners equal to 8.07%. It means that 1163 companies operating in CZ-NACE H had higher ROE than 8.07% in 2017 and they were creating the positive economic value added for their owners. These companies represent the healthy group for this research and further verification.

**Table 2.** Sample selection

| | Healthy companies |
|---|---|
| Total availability for 2017 | 2352 |
| Positive ROA | 1697 |
| ROE exceeding minimal requirement | 1163 |

Source: author

## 4. RESULTS

Results for all models predicting financial distress introduced in chapter 2 have been computed. The gained evaluation of individual companies contained in data sample explained above will be shown in this chapter. The interpretation will follow the division of the sample to the defaulted and non-defaulted companies. Most models can be interpreted together because they use for the classification two or three zones – unhealthy, grey and healthy group. Exceptions are Grünwald model, Bonita and R model, which will be evaluated separately. The reason is that these models were created with more than three classification zones. The results will be displayed in tables containing absolute numbers of the classified companies belonging to each model zone and relative indicators as reliability and error rate. Reliability shows the percentage of the companies that was evaluated perfectly and error rate represents the percentage of the companies that were evaluated totally imperfectly. The definition of these indicators was explained in the part Research methods.

**Table 3.** Explaining power in the case of defaulted companies

| Model | Unhealthy | Healthy | Grey Zone | Not evaluated | Reliability | Type I Error |
|---|---|---|---|---|---|---|
| Altman | 21 | 7 | 2 | 0 | 70.00% | 23.33% |
| IN01 | 21 | 6 | 3 | 0 | 70.00% | 20.00% |
| IN05 | 21 | 7 | 2 | 0 | 70.00% | 23.33% |
| Doucha | 11 | 8 | 1 | 10 | 36.67% | 26.67% |
| Kralicek | 18 | 1 | 5 | 6 | 60.00% | 3.33% |
| Prusak 1 | 18 | 5 | 1 | 6 | 60.00% | 16.67% |
| Prusak 2 | 0 | 0 | 30 | 0 | 0.00% | 0.00% |
| PAN-E | 15 | 5 | 0 | 10 | 50.00% | 16.67% |
| PAN-F | 23 | 7 | 0 | 0 | 76.67% | 23.33% |
| PAN-G | 23 | 7 | 0 | 0 | 76.67% | 23.33% |
| D2 | 23 | 6 | 0 | 1 | 76.67% | 20.00% |
| D3 | 20 | 4 | 0 | 6 | 66.67% | 13.33% |
| Hajdu and Virag | 5 | 25 | 0 | 0 | 16.67% | 83.33% |
| Šorins/Voronova | 26 | 4 | 0 | 0 | 86.67% | 13.33% |
| Merkevicius | 25 | 5 | 0 | 0 | 83.33% | 16.67% |
| Taffler | 25 | 4 | 0 | 1 | 83.33% | 13.33% |

Source: author

The table monitoring the defaulted companies proves that there are significant differences among the used models predicting financial distress. It must be noted that these models have already demonstrated a high explanatory power on other samples. This cannot be confirmed for the sample used here. Some models maintain their high explanatory power, some have a moderate one and there are also several models with poor results. Setting reliability and error rate aside for a while, we will focus on the number of unevaluated companies. Models Doucha and PAN-E are not able to evaluate 10 companies which represent one third of the data sample. Also models such as Kralicek, Prusak 1 and D3 have a higher proportion of the companies whose financial data cannot be evaluated. Such a result does not mean that the model provides incorrect answers for the decision making but it notifies the user that the model cannot work properly because of financial items equal to zero. On the other hand such a result does convey anything to the reader. Focusing on Type I Error, the worst results are connected with the model of authors Hajdu and Virag whose error rate exceeds 80%. No results are provided by Prusak 2 because all companies belong to the grey zone although in reality there was the insolvency proposal in each case. Quite a high error rate and low reliability rate are valid for the Doucha approach which has been already mentioned because of the high proportion of unevaluated companies. Extremely good results are connected with the models of Šorins/Voronova, Merkevicus and Taffler whose reliability rate exceeds 80%. Almost the same results have been achieved by the models PAN-F, PAN-G and D2 (reliability rate 76.67%). Unmentioned models as Altman, IN01, IN05, Kralicek, Prusak 1 and D3 have the reliability rate higher than 50% but not reaching 80% because of wrong classification, usage of grey zone or impossibility of evaluation. The group containing the defaulted companies is only one part of the sample and therefore the model has to have also high reliability rate for the non-defaulted companies.

The table containing the final evaluation for non-defaulted companies will prove or disprove the results gained previously for defaulted entities. Higher proportion of impossible evaluation is repeated in the case of the models Doucha and PAN-E. Both models reach a very high reliability rate. The model created by Hajdu and Virag has one of the highest reliability rates but we have to take in mind that this model reaches the highest error rate in the case of the defaulted companies. It can be concluded that this model is too soft and classifies the majority of companies as healthy without respecting their real financial situation.

No model has a reliability rate below 50% but some models are very close (IN01, Prusak 1 and Prusak 2). The models created by Prusak also have quite a high error rate in comparison with the other used prediction approaches. The reliability rate exceeding 90% can be observed in the case of the models PAN-E, PAN-F, PAN-G, D2, Hajdu and Virag. It must be noted that the models PAN-E and Hajdu and Virag do not provide relevant answers for the defaulted entities and therefore they will not be a part of the final recommendation. The previous sample adored the approaches of Šorins/Voronova, Merkevicus and Taffler. The results for Merkevicius dropped significantly but Šorins/Voronova and Taffler reach almost 80% reliability rate but their error rate shows dissatisfaction.

The tables dedicated to the defaulted and non-defaulted companies do not contain the results for the models Grünwald, Bonita and R. These models differ in the classification zones and therefore each will have their individual evaluation tables. The weakness of Grünwald model is the high proportion of the companies which cannot be evaluated. It is mainly caused by the indicator interest coverage defined as EBIT/interest. When the company does not use any debts connected with the interest than the item interest is equal to zero and the ratio cannot be computed. The model itself does not have a high error rate for both samples but it is not useful because it does not provide an answer in many observed cases.

**Table 4.** Explaining power in the case of non-defaulted companies

| Model | Unhealthy | Healthy | Grey Zone | Not evaluated | Reliability | Type I Error |
|---|---|---|---|---|---|---|
| Altman | 58 | 795 | 309 | 1 | 68.36% | 4.99% |
| IN01 | 24 | 636 | 494 | 9 | 54.69% | 2.06% |
| IN05 | 52 | 769 | 333 | 9 | 66.12% | 4.47% |
| Doucha | 9 | 898 | 168 | 88 | 77.21% | 0.77% |
| Kralicek | 106 | 783 | 265 | 9 | 67.33% | 9.11% |
| Prusak 1 | 196 | 692 | 258 | 17 | 59.50% | 16.85% |
| Prusak 2 | 216 | 598 | 340 | 9 | 51.42% | 18.57% |
| PAN-E | 28 | 1047 | 0 | 88 | 90.03% | 2.41% |
| PAN-F | 36 | 1118 | 0 | 9 | 96.13% | 3.10% |
| PAN-G | 84 | 1070 | 0 | 9 | 92.00% | 7.22% |
| D2 | 17 | 1137 | 0 | 9 | 97.76% | 1.46% |
| D3 | 187 | 967 | 0 | 9 | 83.15% | 16.08% |
| Hajdu and Virag | 17 | 1137 | 0 | 9 | 97.76% | 1.46% |
| Šorins/Voronova | 237 | 925 | 0 | 1 | 79.54% | 20.38% |
| Merkevicius | 418 | 744 | 0 | 1 | 63.97% | 35.94% |
| Taffler | 231 | 923 | 0 | 9 | 79.36% | 19.86% |

Source: author

**Table 5.** Explaining power of Grünwald model

| | Defaulted companies | Non-defaulted companies |
|---|---|---|
| Unhealthy | 6 | 43 |
| Weaker | 0 | 9 |
| Good | 0 | 22 |
| Extremely good | 0 | 323 |
| Not evaluated | 24 | 766 |
| Reliability | 20.00% | 27.77% |
| Error | 0.00% | 3.70% |

Source: author

Grünwald model uses four evaluation zones and Bonita model uses originally even eight evaluation zones. The problem is not that some cases should not be evaluated, there is a much more serious issue. In the case of the defaulted companies the model classified a sample incorrectly because the error rate reaches 50%. It can be interpreted that the user will gain the results in a worse fashion than coin flipping. Bonita model does not have a high accuracy rate for fulfilling the forecasting purpose.

**Table 6.** Explaining power of R model

| | Defaulted companies | Non-defaulted companies |
|---|---|---|
| Low danger | 6 | 935 |
| Slight danger | 2 | 17 |
| Medium danger | 1 | 23 |
| High danger | 0 | 12 |
| Extremely high danger | 20 | 175 |
| Not evaluated | 1 | 1 |
| Reliability | 66.67% | 81.86% |
| Error | 26.67% | 16.08% |

Source: author

The last atypical model is R model using five evaluation zones. This model does not have any serious weakness. Only one defaulted and one non-defaulted company cannot be evaluated. The error rate is not extremely high for neither of the two samples. Especially the results for the group of the non-defaulted companies are quite good because the reliability rate is higher than 80%. This cannot be confirmed for the second sample. The reliability rate for the defaulted companies is lower and it reaches almost 67%. The models whose results have been introduced above have better accuracy and therefore R model will not be a part of the final recommendation.

**Table 7.** Explaining power of Bonita model

| | Defaulted companies | Non-defaulted companies |
|---|---|---|
| Extremely good | 12 | 384 |
| Very good | 2 | 185 |
| Good | 1 | 241 |
| Moderately good | 0 | 196 |
| Poor | 0 | 148 |
| Slight threaten | 1 | 4 |
| Threaten | 2 | 1 |
| Extremely threaten | 11 | 1 |
| Not evaluated | 1 | 3 |
| Reliability | 46.67% | 69.65% |
| Error | 50.00% | 0.52% |

Source: author

This paragraph will sum up conclusions gained for the defaulted and non-defaulted companies. It is necessary to find the models predicting financial distress which have a high explanatory power for both types of companies. When forecasting is done the user does not know which companies are defaulted and which are non-defaulted. This answer should be provided by the forecasting itself. For practical use, the following models should be recommended – PAN-F, PAN-G, D2, Šorins/Voronova and Taffler. The weaknesses of other models have already been discussed.

## 5. CONCLUSION

This paper used the models predicting financial distress for forecasting corporate financial health. Selected models proved their accuracy in the past but it was for other kinds of data samples. The specificity of this research lies in the sector of economic activity. The analysed companies belong to the group CZ-NACE H which contains companies operating in transportation and storage. Many tested models have not reached enough accuracy and therefore cannot be recommended for further use. On the other hand, a group of models predicting financial distress have been detected, which have enough accuracy for companies belonging to the transportation and storage. PAN-F, PAN-G, D2, Šorins/Voronova and Taffler are the models which had a high explanatory power for the analysed data samples.

While we found models which can be recommended for practical use, this research also illustrates the specificity of the economic sector Transportation and storage. Many models with good results for the manufacturing or construction failed. It proves that there is a need for further research in this area and introduces a possibility for the model constructed especially for this economic sector in the Czech Republic.

This paper proves that a model's universality is a problem. This statement has broader implications for the general evaluation of the financial situation. Governmental bodies should not use one universal model in case when the applicants of the subsidies are evaluated. Managers from corporate sector should also reflect their company's specifics as is the belonging to the industry branch in this case.

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