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PREFACE

Dear readers,

It is my pleasure to introduce you a collection of papers from the 15th annual international scientific conference The European Financial Systems 2018 organized annually by Department of Finance of the Faculty of Economics and Administration, Masaryk University in Brno, Czech Republic. This year's conference was focused especially on the current issues related to accounting, banking sector, insurance, financial literacy, financial law, new regulations of financial markets, different tax systems, corporate finance, cryptocurrencies, public finance and financing of non-profit organizations.

Since the collection of papers presents the latest scientific knowledge in this area, I believe you will get a number of new insights usable both for your scientific, and educational or practical activities. I would also like to express my strong conviction that we meet each other in occasion of the 16th year of this conference held in 2019.

I wish you pleasant reading!

Petr Valouch

Chairman of the Program Committee

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Using of Non-financial Data in Predictive Models

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Abstract: *Forecasting the company's future economic situation arose in the early 20th century. First of all, a multidimensional discriminatory analysis was used to construct prediction models, later replaced by logistic regression. The new challenge in predicting financial development is neural networks representing a more reliable financial forecast compared to mathematical and statistical methods. The neural network, by mimicking the capabilities of human brain neurons, is capable of modeling the course of dependencies between individual indicators and results. A disadvantage of the original prediction models is also the low range of empirical accounting data and the fact that they are focused only on financial data. The introduction of the financial statements registers led to the possibility of free access to full data from the financial statements, which opens the door to new possibilities in scientific research. For the purpose of this paper an annual report of 20 selected companies were tested. The aim of this paper is to accept or reject the claims that non-financial „narrative" data could be also used for the assessment of the financial position and financial performance of the companies. The results of our sentiment analysis supported the hypothesis that financially distressed companies use a different tone of language in their annual reports compared to financially stable companies. These findings confirmed the relationship between the tone which managers use in constructing annual report narratives, and the financial performance of the company. Therefore, it is advisable to incorporate non-financial data into the forecasting models.*

Keywords: financial statements, financial analysis, neural network, deep learning, data mining

JEL codes: M49

1 Introduction

The goal of financial analysis is to recognize what is bad and good for the business, which can cause problems in the future, and vice versa, to identify its strengths that can be relied upon in the future (Šlosárová, 2014). The forecasting of the financial situation of enterprises is considered to be a relatively young area of scientific research, which dates back to the 30s of the 20th century. At the beginning experts predicted the future financial situation by comparing financial ratios. Beaver (1966) examined the financial indicators on the basis of a one-dimensional discriminatory analysis. There are known following prediction models - Altman (1968), Deakin (1972), Ohlson (1980), Taffler (1982) or Zmijewski (1984).

At the end of the 1960s, multidimensional discriminatory analysis began to be used for forecasting. Based on the multidimensional discriminatory analysis, it was the first model of the Altman (1968) predictive model for publicly-traded joint stock companies (the so-called Model Z-score) which some other theoreticians and practitioners have already been

taking in the short time, Deakin (1972) and Blum (1974). In the 1980s, logistical regression was gradually brought to the forefront of financial forecasting research, which gradually replaced multidimensional discriminatory analysis. First, he used logistic regression to create a model to predict the future financial situation of Ohlson (1980).

Prognosis of the future situation of a business entity through methods of multidimensional discriminatory analysis and logistic regression is very widely used, but in reality, when predicting company failures, these methods have certain limitations that largely result from their very nature. One of the basic assumptions of multidimensional discriminatory analysis and logistic regression is dichotomic dependent variability. What requires groups of companies with a good financial situation and an unsatisfactory financial situation to be clearly defined and clearly distinguishable. In practice, however, this assumption is very difficult. The problem is the very definition of defaulting companies, from which the classification of the companies on which the prediction model is based depends. Most models use a sample composed of two priority groups "unsuccessful" and "successful" companies. Models constructed on the basis of multidimensional discriminatory analysis and logistic regression have limitations that relations between financial ratios are unstable over time and, due to changes in inflation, economic cycles in a given country, interest rates. instability over time leads to a change in the set coefficients of the ratios or changes in the boundary classification values. The disadvantage of these approaches is also the low scope of empirical accounting data, moral wear and tear in countries where these analyzes were directly related and further low usability in the conditions of the Slovak Republic, as they use data which have a low prediction ability in the Slovak environment or some data are not available at all (for example, market price of shares). These facts should lead to regular testing of the model and its re-verification, if necessary.

One of the first studies dealing with the comparison of neural networks (NN) with classical mathematical and statistical techniques in forecasting the financial development of enterprises was the Odom and Shard study of 1990. Neural networks represent one of the areas of machine learning. By machine learning, we mean a set of methods and approaches that allow the machine to learn. The system's knowledge gains from the training set of data. This system (in our case the neural network) should also have the ability to generalize.

In 2015, Blanco-Oliver published a collection of study authors focusing on creating a model for micro-accounting units. They introduced non-financial information into the model and constructed it using neural networks. In this study, we conclude that predicting bankruptcy through neural networks can achieve greater predictive power and lower cost of classification errors than with logistic regression and the introduction of non-financial variables improves the predictive precision of models. According to this study, the introduction of neural network access and the introduction of non-financial variables are two important means to improve the predictive precision of predictive models (Blanco-Oliver, Irimia-Dieguez, Oliver-Alfonso, Wilson, 2015).

A very large number of published studies to compare classical mathematical and statistical methods with neural networks confirm the conclusion that neural networks are better suited to predicting bankruptcy and have significantly higher predictive precision than logistic regression or multidimensional discriminatory analysis. The introduction of non-financial or macroeconomic variables into the model through independent indicators greatly improves the predictive precision of the model and the use of any method to model. It is not necessary to note that questions about modeling through neural networks such as the integration of data mining methods, the selection of suitable parameters, the selection of functions, a wide range of different techniques, etc., which are currently not universally and sufficiently relevant, are still open based on previous research, and should therefore do research in the future to answer these questions.

Machine learning is widely used nowadays to review contracts, leases, invoices, and other documents. The adoption of machine learning within the accounting profession is still, admittedly, at an early stage. To accelerate the wider use of this technology, it is necessary to create economies of scale by integrating its cognitive capabilities in the areas of textual

analysis, voice recognition, image and video parsing, and judgment support into the financial analysis and audit process. This article discusses how the cognitive capabilities of machine learning of non-financial data from annual reports could be applied to financial analysis and predictive models and to enable improve decision making.

2 Methodology and Data

For the purpose of this paper we analyzed annual reports of companies divided into two groups based on Altman's bankruptcy prediction model: financially distressed companies likely to go bankrupt within the following two years and financially stable companies with the high probability to survive. This model proposed bankruptcy based on financial ratios based on current financial results. We examined whether the qualitative information contained in annual report narratives indicated the bankruptcy alongside this quantitative information. Thus, we analyzed whether companies likely to go bankrupt employed a different tone of language compared to financially stable companies.

For this purpose, we selected 20 companies out of the Fortune 1000 list (Fortune, 2018). We divided them into two equal groups according to Altman's Z-score obtained from the Factiva database portal. Further, in order to obtain the data, we collected annual reports, 10-K filings, of U.S. companies from the EDGAR database (EDGAR, 2018). In total, we examined 20 annual reports for the fiscal year 2016.

Table 1: Companies Classified into the "Distress Zone" According to Altman's Z-score

Rank	Company	Z-score	Industry (SIC)
1.	Anadarko Petroleum Corp.	0,71	Crude Petroleum and Natural Gas
2.	Apache Corp.	0,55	Crude Petroleum and Natural Gas
3.	Caesars Entertainment Corp.	-0,24	Hotels and Motels
4.	Darling Ingredients	1,53	Animal and Marine Fats and Oils
5.	Freeport-McMoRan, Inc.	0,22	Copper Ores
6.	Leucadia National Corp.	0,46	Investors, NEC
7.	Post Holdings, Inc.	1,06	Cereal Breakfast Foods
8.	The ADT Corp.	0,99	Security Systems Services
9.	WestRock Co.	1,35	Die-Cut Paper and Paperboard and Dardboard
10.	Windstream Holdings, Inc.	0,62	Telephone Communications

Source: Factiva Companies and Executives, 2018

The following table lists the "safe zone" companies, the industries in which they operate, and their Altman's Z-score:

Table 2: Companies Classified into the "Safe Zone" According to Altman's Z score

Rank	Company	Z-score	Industry (SIC)
1.	Applied Materials, Inc.	4,17	Semiconductors and Related Devices
2.	Campbell Soup	3,19	Canned Specialties
3.	Cisco Systems	3,14	Telephone and Telegraph
4.	Citrix Systems, Inc.	3,83	Pre-packaged Software
5.	Exxon Mobil	3,72	Petroleum Refining
6.	Johnson & Johnson	5,09	Pharmaceutical Preparation
7.	McDonalds Corp.	5,25	Eating and Drinking Places
8.	PepsiCo, Inc.	4,01	Bottled and Canned Soft Drinks
9.	Phillips 66	3,56	Petroleum Refining
10.	The Walt Disney Co.	4,5	Motion Picture and Video Production

Source: Factiva Companies and Executives, 2018

Although the companies were selected across various industries, we attempted to choose similar industries within both the safe zone and distress zone. This would help us to prevent the situation where industry-specific attributes would undermine the results as some words are more characteristic for some industries than others. Thus, the companies within both groups operated in telephone communication, the food sector, entertainment, petroleum refining, and security systems and software.

To assess the sentiment used in annual report narratives, we processed and analyzed this data with the LIWC2015 (Linguistic Inquiry and Word Count) textual analysis program. This program analyses text on various sentiment categories, including positive emotions, negative emotions, certainty, risk focus and others.

Linguistic Inquiry and Word Count (LIWC) is a text analysis computer program that provides output in the form of a percentage of the words contained in the text from the categories mentioned. For example, if the text contains 1,000 words, the dictionary might find 50 words which occur in the text express positive emotion, so then it allocates score 5 to positive sentiment. Thus, within each category the score ranking from 0 to 100 may be attributed to the specific text. The more words the software analyses, the more reliable the results are. As our samples contained texts ranging from 7,000 to 22,000 words, we consider the results obtained to be reliable (LIWC, 2018).

We employed this computer-assisted dictionary in order to analyze the sentiment aspect of annual report. Each of the companies was, firstly, analyzed individually on several categories of sentiment. Then we synthesized the results obtained for "distress zone" companies and "safe zone" companies in order to get the full picture about the differences between these two.

3 Results and Discussion

Although the idea of artificial neural networks dates back to the 1950s, such networks could not be called real artificial intelligence until recent advances in computational power and data storage enabled the development of deep neural networks that model the structure and thinking process of the brain. The hidden layers of a deep neural network automatically "learn" from massive amounts of data (especially semi-structured or unstructured data) received by the input layer (e.g., also images, annual reports, text files), recognize data patterns in more and more abstract representations as the data is processed and transmitted from one hidden layer to the next, and classify the data into predefined categories in the output layer.

Deep learning algorithms further enrich financial analysis by identifying related concepts or topics, recognizing entities (e.g., people, place, events, companies), extracting emotions (e.g., anger, joy, sadness, disgust), and understanding subject-action-object relationships. In addition, they can link concepts to a document and tag them accordingly. Deep learning technology—an emerging form of artificial intelligence that can be trained to recognize patterns in vast volumes of data that would be impossible for humans to process. This still evolving technology represents a way to utilize big data to create supplementary audit evidence that improves the effectiveness and efficiency of audit automation and decision making.

For example, financial analysts can select data attributes in order to predict bankrupt (auditors can predict fraud); the selected attributes are then combined with traditional financial or nonfinancial data fields to develop a new deep learning prediction model. Deep learning performs as an appropriate prediction algorithm in this case because, by introducing the extracted attributes, the number of predictors is much larger than what a traditional machine-learning algorithm could process. For each assertion, the output of the model could be the predicted risk level or suggested follow-up tests, depending upon the nature and the label of the training data.

For the purpose of this paper, we analyzed the companies according to the Altman Z-score to find out whether the qualitative information expressed in narrative reporting differs between companies with a high probability of bankruptcy and those in a financially stable

position. Thus, we could assume that the annual report narratives of financially distressed companies show sentiment which is more negative and more uncertain compared to the financially healthy companies.

We found out that financially healthy companies achieved a slightly higher score on positive sentiment compared to distressed companies (2,79 vs. 2,77). When we examined more deeply the companies themselves, we found that companies from the distressed group which had suffered a loss in fiscal year 2015 employed less positive and more negative emotions than the distress- classified companies which, however, achieved a profit.

However, when we further examined the negative emotion elements, we could see that companies with probable financial problems tended to employ more anxious language compared to the other group (0,26 vs. 0,21). This may be due to the fact that distressed companies are worried about the future because even though they might not fall into financial problems yet, it is likely that they will experience them within the next two years. Thus, they expressed their concerns through this category of words even before the bankruptcy or insolvency appears. However, when we considered only the companies which already suffered a loss in fiscal year 2015 from the distressed group, these have a much lower level of anxiety compared to the rest of the group (0,20 vs. 0,30) and a slightly higher level of certainty (0,79 vs. 0,76).

Interestingly, the financially distressed companies ranked lower on two almost opposing categories: certainty (0,77 vs. 0,84 achieved by the safe group) and tentativeness (1,79 vs. 1,94 achieved by the safe group). Even though these results are relatively surprising, distressed companies with a poorer financial performance were found to be more certain and, at the same time, more uncertain compared to the better-performing companies. It might be caused by the fact that these companies, on the one hand, connect uncertain terms with the financial situation and, on the other hand, the certain terms with activities to handle the poor financial situation. Therefore, in our case, we could use the reasoning that financially distressed firms are less tentative in terms of handling their financial situation, for example, implementing new strategies, restructuring programs, and other initiatives in order to prevent the possible bankruptcy. However, they are still more uncertain referring to their future financial situation compared to companies from the safe zone which can be almost sure they will not experience bankruptcy during future years.

Then the five additional categories were examined. Those are Affiliation, Achievement, Power, Reward focus, and Risk focus. All of them belong to LIWC2015 categorization. They could provide important clues about what specifically drives company performance and/or which categories the managers would like to place the highest emphasis on in their reporting while assessing company financial performance and future trends.

Companies within the safe zone achieve a higher score on the first four categories - affiliation (2,6 vs. 2,5), achievement (1,8 vs. 1,65), power (2,74 vs. 2,69), reward (1 vs. 0,65). The financially distressed companies only outperform them on the risk category (0,96 vs. 1,09). The power category, on which both groups score the highest (2,74 and 2,69) reveals interest in status and dominance. However, this category is likely to comprise words like "boss", "president", or "strong". Thus, it is obvious that such words appear in the annual reports of the companies. Therefore, this category does not have a huge explanatory power for the purpose of our analysis.

What is, however, more interesting is the fact that financially distressed companies already see the higher risk connected with their financial performance, and we can see that this is reflected in the texts of their narratives. Therefore, this analysis might help us to predict the financial performance of the firms to some extent. The full picture which combines the insight into all of these five categories together could, therefore, provide us with some evidence about the worsening financial performance of a company expressed in the textual part of the annual reports.

4 Conclusions

The financial data comprised in annual reports are important indicators of current financial performance and may also indicate future financial development via the application of prediction models such as Altman´s Z- score. However, they do not provide us with insight into all of the circumstances that led to these results, information about future trends, development and managers' expectations. For this purpose, the qualitative data is especially useful.

For the purpose of this paper the annual reports of 20 selected companies were tested. Companies were randomly selected from database Fortune 1000. Their Altman Z-score was obtained from the Factiva database. We have chosen companies across various industries. Firstly, we focused on the tone used by managers when discussing company performance, position and future trends in annual reports. For this purpose, was used computerized text analysis program.

Although annual report narratives are more subjective compared to the financial data, we suggest they may be indicative of future financial developments, as demonstrated by the language managers use to disclose information. In this study we used a textual analysis software in order to accept or reject the claims, that non- financial "narrative" data could also be used for the assessment of the financial position and financial performance of a company. Our analysis focused on the Management Discussion and Analysis section (MD&A) of the 10-K reports. Here managers comment on financial performance, but also express predictive statements about future trends, expectations and challenges. Therefore, the information comprised in these sections indicate future financial performance.

The results of our sentiment analysis supported the hypothesis that financially distressed companies use a different tone of language in their annual reports compared to financially stable companies. These findings confirmed the relationship between the tone which managers use in constructing annual report narratives, and the financial performance of the company. Therefore, it is advisable to incorporate non-financial data into the forecasting models. This can be incorporated into prediction models based on neural networks.

However, the research presented has its limitations that could subsequently affect the reliability and accuracy of the results achieved and on which our recommendations are based it can be possible to eliminate the drawbacks by using neural networks but this requires a bigger data sample and automated input data processing.

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References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, vol. 23(4), pp. 589-609.

Blanco-Oliver, A., Irimia-Dieguez, A., Oliver-Alfonso, M., Wilson, N. (2015). Improving Bankruptcy Prediction in Micro-Entities by Using Nonlinear Effects and Non-Financial Variables. *Finance a Uver: Czech Journal of Economics & Finance 2015*, vol. 65(2), pp. 144-166.

Deakin, E. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research*, vol. 10, pp. 167- 179.

Edgar (2018). *Edgar Company Filings. Retrieved from:* https://www.sec.gov/edgar/searchedgar/companysearch.html.

Factiva (2018). *Factiva: Get Company Snapshot*. Retrieved from: https://global-factiva-com.scd-rproxy.u- strasbg.fr/sb/default.aspx?lnep=hp.

Fortune (2018). *Fortune 500.* Retrieved from: http://fortune.com/fortune500/.

LIWC (2018). *How does LIWC analyse language?* Retrieved from: http://liwc.wpengine.com/how-it-works/.

Odom, M. D., Sharda R. (1990). A neural network model for bankruptcy prediction. In: *Proceedings from IJCNN International Joint Conference Neural Networks*. pp. 163-168. Retrieved from: https://www.researchgate.net/publication/224755073_A_Neural _Network_Model_fo r_Bankruptcy_Prediction

Ohlson, J. A. (1980). Financial ratios and probabilistic prediction of bankruptcy. *Journal of Accounting Research*, vol. 18(1), pp. 109-131.

Ondrušová, L. (2016). Company in crisis form the point of view of accounting. *Journal of East European Science and Research: scientific peer-reviewed journal*, vol. 8(1), pp. 338-345.

Šlosárová, A. (2014). *Analýza účtovnej závierky*. Bratislava: Ekonóm.

Taffler, R. J. (1982). The Z-score approach to measuring company solvency. *The Accountant`s Magazine*, pp. 22-24.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, vol. 22, pp. 59-82.