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Contact to corresponding author: lucia.svabova@fpedas.uniza.sk; Department of Economics, Faculty of Operation and Economics of Transport and Communications, University of Zilina, Univerzitna 1, 010 26 Zilina, Slovakia

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Lucia Svabova
University of Zilina, Slovakia
orcid.org/0000-0002-4722-4103

Katarina Kramarova
University of Zilina, Slovakia
orcid.org/0000-0001-6883-3541

Jan Chutka
University of Zilina, Slovakia
orcid.org/0000-0003-2501-6415

Lenka Strakova
University of Zilina, Slovakia
orcid.org/0000-0002-9743-4934

Detecting earnings manipulation and fraudulent financial reporting in Slovakia

JEL Classification: *C52; D22; M41*

Keywords: *Beneish model; discriminant analysis; earnings manipulation; fraudulent financial reporting*

Abstract

Research background: Misleading financial reporting has a negative impact on all stakeholders since financial records are the primary source of information on financial stability, economic activity, and financial health of any company. The handling of them is primarily the responsibility of managers or owners and reasons for doing so may differ. Their common denominator is the artificial creation of information asymmetry to get different types of benefits. It is, therefore, logical that the issue of detecting opportunistic earnings management comes to the fore.

Purpose of the article: The purpose of the study is to create a discriminant model of the detection of earnings manipulators in the conditions of the Slovak economy.
Methods: We used the discriminant analysis to create a model to identify fraudulent companies, based on the real data on companies that were convicted from misleading financial reporting in connection with tax fraud in the years 2009–2018. The model is inspired by the Beneish model, which is one of the most applied fraud detection methods at all.
Findings & Value added: In order to achieve more accurate detection results, we extended the original model by taking into account the values of indicators from three consecutive years, i.e. by taking into account the development of the potential tendency of companies to be involved in opportunistic earnings management. Our model correctly identified 86.4% of fraudulent companies and overall reaches 84.1% classification ability. Both models were applied on empirical data on 1,900 Slovak companies from the years 2016–2018, while their overlap was 32.7% for fraudulent companies and 38.4% for non-fraud companies. This is a very useful result, as the application of both models rein-forces the results obtained and the identical classification of the company into fraudulent indicates that the manipulation of earnings occurs with a high probability.

Introduction

Under national and international accounting and reporting standards in force, the financial records should provide true and relevant information, since the accounting unite is required to record all economic transactions in such a way that the financial records will present a true and fair view of the facts that are the subject of accounting. The way of reporting economic transactions clearly indicates earnings quality and financial stability of the company. Financial reporting, i.e. the disclosure of financial results and related information to any stakeholders regardless of their interest in the company, falls within the competencies of top management or owners of the company (provided that the owner structure also represents the company´s management body). The incorrectly presented information is either an unintentional error, which results in a violation of applicable legislation or a wilful activity to obscure information about the actual economic activity and financial stability of the company. When financial records are controlled or handled for one’s own benefit, especially in an unfair manner outside the legal framework towards drawing a more positive and optimistic picture, earnings are simply managed (Kaya & Turegun, 2017; Weil *et al*., 2013).

The way of reporting information and related earnings quality is an integral part of earnings management. It is efficient if managers signal financial information to external users to assist them to improve their understanding of the company’s current or upcoming performance (Kaya & Turegun, 2017). However, earnings management is perceived rather negatively — as an opportunistic behaviour of managers, who act for purposes other than that of enhancing truthful reporting (Beneish, 1999; Healy & Wahlen, 1998; Kaaya, 2015; Kramarova & Valaskova, 2020; Meek & Thomas, 2003; Valaskova & Durana, 2020).

The line between appropriate techniques of earnings management and “cooking the books”, i.e. earnings manipulation, can be a blurry one, notwithstanding the abundance of legal rules that are currently in place to deter malfeasance (Willey, 2019). Healy and Wahlen (1998) specifically state that opportunistic earnings management occurs when managers use their judgment in financial reporting and in structuring transactions to alter the reports to mislead stakeholders about the underlying economic performance of the company or even to influence contractual outcomes that depend on reported accounting numbers. In connections with earnings management and agency theory, Sajnog (2019) sees the level of remuneration for managers as a significant problem, as well as emphasizes that inappropriate managers pay policies have also been identified as one of the key factors leading to the financial crisis. Marinakis (2011) confirms that earnings manipulation usually results from escalating earnings management, which after a certain stage violates accounting standards in force. The author states that earnings management and accounting fraud involve common component, which is a manipulation of financial information through earnings manipulation for achieving certain results.

The issue of earnings manipulation is a relatively frequently examined problem between academics and experts directly from practice (Homola & Pasekova, 2020; Pasekova *et al.*, 2019). At present, there are various statistical methods or techniques of data collection that try to identify hidden, unusual or divergent patterns indicating financial fraud. These are various analytical models used to detect possible errors and fraud in accounting and financial reporting. This contribution aims to follow up on this fact and verify the detection ability one of the most well-known detection model — the Beneish model in the conditions of Slovakia and subsequently to create own discriminant model based on financial indicators used by Beneish with a sufficiently strong detection power.

The contribution is structured as follows. The theoretical side of the contribution including the review of relevant literature is presented in the second chapter. The methodology of the study is presented in the third chapter. The chapter includes information on our approach to identifying manipulators and information on creating data sample on companies including information on the training dataset. We also present there the theoretical background of the Beneish model, which is the inspiration of our study and the methodological procedure of model creation in the conditions of the Slovak business environment. The model itself, including the results of its detection power, is presented in the fourth chapter. In the discussion part, we compare the detection ability of the Beneish model and the model created by us. We also apply both models on a larger data sample and analyse their detection match in identifying earnings manipulators. We also list the strengths and weaknesses of our study and its possible further direction. The conclusion summarizes the main finding of the study.

Literature review

As Kramarova and Valaskova (2020) and Pasekova *et al.* (2019) state, the reasons behind fraudulent financial reporting are different, including bias wrecker of tax duties. At the same time, Kramarova and Valaskova (2020) state that in the case of Slovakia, the main reason for fraudulent financial reporting is precisely this fact. According to the study of (Habib & Hansen, 2008), opportunistic earnings management is in close relation with the positive accounting theory and political costs, which parts is also the issue of the tax burden of the business environment, which they consider one of the incentives of company accounting choices. Their findings are consistent with the findings of Cook *et al.* (2008), who suggest that tax expense is an incentive for companies to manipulate earnings since the income tax is seen as an unproductive outflow of capital sources. This fact was also indicated in other studies. E.g. Swiderski *et al.* (2010) confirmed that private companies in Poland, Czechia, and Hungary (countries historically and economically related to Slovakia) aggressively managed earnings downward to avoid higher tax expenses. Callao *et al.* (2017) came to the same conclusion in these countries, including Slovakia. The reasons for this fact can be various; we assume that it may be related to the level of tax and levy burden and the overall quality of the business environment in these countries. The study of Wang and Chen (2012) also confirms that tax avoidance is one of the incentives for earnings manipulation. However, the level of susceptibility is different among companies, e.g. companies in good financial condition have relatively lower tax burden, which influences weakening the tax-avoidance motivation in earnings management. Beaver *et al.* (2007) presented the analysis of the distribution of pre-tax earnings and special items and identified the incoherence in the distribution of earnings due to asymmetric effects of income taxes and special items for profit companies and loss companies. They conclude that income taxes pulled earnings toward zero, while negative special items pull loss observations away from zero. On the other side, they do not challenge the potential impacts of other factors on the companies' earnings distribution and manipulation.

In general, the basic framework of control the reporting economic transactions falls within the competence of internal control or internal audit of each company. The empirical studies have found that internal control can reduce the probability of frauds, so the weakness of the governance system is an important factor determining financial statement fraud (Jensen, 1993). Its organization and scope are logically determined primarily by the size of the company, especially in the context of the financial volume of reported transactions. It should include both control ex-ante (control before the accounting case is recorded) and ex-post (control of already recorded accounting case) and internal audit (continuously). The external level of control may be performed under the request of the audited entity (i.e. voluntarily) or another entity that may be interested in the audited entity. In the case of Slovakia, the external level of control of a compulsory nature includes auditing of financial statements if the company is given this obligation by law (according to the Section 19, paragraphs 1–4 of the Act No. 431/2002 Coll. on Accounting as amended) and control performed at the initiative of the public authority (e.g. tax authority) (Kramarova a& Valaskova 2020).

According to Gill (2004), the basic level of external control should be the financial statement analysis including its basis methods — horizontal and vertical analysis, since they may be helpful in discovering and examining unexpected relationships in financial data presented in the financial statements. Financial statement analysis based on financial ratios is also valuable in finding errors or fraud in financial statements (Pasekova *et al*. 2019). E. g. the study by Pasekova *et al.* (2019) revealed that the most preferable ratios in Czechia were indebtedness, liquidity, profitability, and activity ratios. EBITDA seems to be significant for mainly managerial decisions. Overall, the financial statement analysis is based on the premise that relatively stable relationships exist among economic events in the absence of conditions to the contrary. This fact is taken into account also by sophisticated detection techniques of opportunistic earnings management and fraudulent financial reporting. In this connection, an irreplaceable role is also played by the quality of accounting standards, whether of national or international character (Homola & Pasekova, 2020).

Marinakis (2011) states that there are three main research approaches to this issue — conditional distribution models, discretionary accruals models, and specific accruals models.

Methods based on the distributional approach (e.g. Beatty *et al*., 2002; Burgstahler & Dichev 1997; Dichev & Skinner 2002; Hayn 1995; Healy & Wahlen 1998; Leuz *et al*., 2003; Shuto, 2008; Van caneghem, 2002 etc.) try to detect any irregularities in earnings patterns, which represent any discontinuities around specific reference points. The approach applies a logical hypothesis that managers have incentives related to meeting or beating certain earnings benchmarks (bottom-line figures, analysts' forecasts), so the approach calculates with the assumption that any significant incoherence in the earnings distribution around these benchmarks results from managerial manipulation of accounting numbers. Degeorge *et al.* (1999) take a view that focusing on the manager on bottom-line figures as a key measure of financial strength and economic potential is logical, since all stakeholders do that.

A different view is applied in two other approaches; however, they are still strongly linked to the information in financial reports. Both are based on managing accruals, where accruals are seen as the result of reporting economic transactions representing the difference between cash flows from the operating activities and net income. Non-discretionary accruals (economical accruals) are accepted by accounting standards and accounting entities are even required to account them. Discretionary accruals (managerial accruals) are created deliberately to manipulate changes in the reported earnings and are alternation to cash flows selected purposefully by managers (Das & Jena, 2016; Li & Moore, 2011; Sapar, 2008).

Discretionary based models (aggregate accruals models; e.g. Dechow *et al.*, 1995; Francis *et al.*, 2005; Healy, 1985; Jones, 1991; Kothari *et al.*, 2005) in general try to find a way of appropriate differentiation between discretionary and non-discretionary accruals by using statistic methods, mainly regression analysis. The models generally follow the suggestion by (Kaplan, 1985) that accruals decisions likely result from the exercise of managerial discretion and changes in the company´s economic conditions. Specific accrual models generally react on aggregate accruals models misspecification, which has occurred in practice. By examining specific accruals, models may provide direct evidence for standard setters and regulators of areas where standards work well and where there may be room for improvement. As a secondary benefit, studies on specific accruals may be able to develop more powerful models (Marinakis, 2011).

The model by Beneish (1999) is probably the most well-known model detecting earnings manipulation by accepting a systematic relationship between the probability of manipulation and specific accruals. The model itself examined fraudulent reporting in companies, which have been proven violating the GAAP. Beneish thinks that in addition to total accruals, more existing variables can indicate the presence of fraudulent activity. The model is being widely applied by researchers from many countries and its detection ability is being tested in the conditions of national economies.

In Slovakia, studies in the field of earnings manipulation are still relatively rare (regardless of the selected approach). This issue is addressed, e.g. by the studies of (Durana *et al*., 2020; Kovalova & Frajtova Michalikova, 2020; Papik & Papikova, 2020; Podhorska *et al*., 2019; Svabova *et al*., 2020; Valaskova & Durana, 2020). We dare say that a detection model of earnings manipulation which would accept specifics of the Slovak business environment has not yet been created in Slovakia. From this point of view, we consider our study innovative and able to fill this identified scientific gap.

Research methodology

General overview

In this study, we followed the Beneish´s research (Beneish, 1999), and we applied his model to the conditions of the Slovak business environment. We tested its detection power on a sample of companies (the training sample) that we knew about that were performing fraudulent financial reporting in connection with tax fraud. Subsequently, we created a new detection model.

Based on the same premises as Beneish did, we supposed that financial indicators used in the model, calculated as on-year indexes, were capable special variables to spot discrepancies in financial reports and to reveal opportunistic earnings management. To improve the detection ability of our model in contrast to Beneish, we decided to consider also the company´s potential tendency to manipulate earnings that we expressed as indexes of the variables for three consecutive years ending in the year in which the company demonstrably committed earnings manipulation to avoid its tax liability. I.e. each original variable is quantified as two different time indexes. The tax fraud, for the need of the study, we categorized as an administrative offence and the given companies were obliged additionally to pay a tax and penalty.

To create a detection model applicable to the Slovak companies, we used the method of discriminant analysis. Our aim was not to find a set of variables that would be significant in the created model (therefore, we retained all the variables used by Beneish), but estimate the discriminant score, i.e. manipulation score (M-score_{svk}) for correct classification of companies to the group of fraudulent/non-fraud companies as accurate as possible. We used the approach applied in the counterfactual evaluations (e.g. (Blazkova & Dvoulety, 2019; Rosenbaum & Rubin, 1983, 1985; Stuart, 2010), where the quality of the model as a whole and the significance of individual variables are not directly analysed, but the focus is given at the most accurate detection by implementing a higher number of variables in the model. We performed all calculations using the SPSS 25 software; the tables in the annex are the outputs of the procedures in this statistical software.

Determining criteria "fraudulent/non-fraud company" and sample selection

The training sample consists of 44 companies — 22 fraudulent and 22 non-fraud companies. All of them reported economic transactions following the Slovak accounting and reporting standards in the observed period. None of the companies has the character of a publicly-traded company on the stock exchange.

Table 1 and Table 2 show the numbers of companies in terms of their size and economic activity (SK NACE classification). This small sample of companies (especially of fraudulent companies) can be considered as a weakness of our study, but the results are strengthened by the application of bootstrapping. We applied bootstrapping to the training sample and obtained 2,000 observations, which were used to valid detection (discriminatory) power of the M-score$_{svk}$. Apart from that, given the size of the national economy, studies by several authors were conducted on a relatively equal or similarly large sample of companies (Beneish, 1999; Irwand *et al*., 2019; Ozcan, 2018; Ramirez-Orellana *et al*., 2017; Ramirez-Orellana *et al*., 2017).

The sample of non-fraud companies represents the companies that we believe in the rate of their misleading reporting is very low. We minimized the risk to select wrong companies in several control steps, starting with checking the formal correctness of their financial reports, including the quick analysis of the information provided in the notes to the financial reports. From the possible group of companies, we automatically excluded companies that were kept in the register of tax debtors of the Financial Administration of the Slovak Republic and other public administration institutions (health, social insurance). We also excluded companies that were in the process of liquidation, restructuring or were declared bankrupt (all to 2018). We verified all these facts through the Finstat Database, the Business Register of the Ministry of Justice of the Slovak Republic and the Bankruptcy Register. In overall, we know that accounting of 20 companies is being outsourced, thereby under external control, and we, therefore, assume that the rate of misleading financial reporting in their case has also been minimized. Two companies have been subject to an external audit for a long time following Slovak accounting legislation in force. Two other companies do not show errors in the formal accuracy of the financial statements and do not show significant fluctuations in their economic development without consistent qualitative changes. One company was the subject of the control by the tax authority without any findings in the accounting and tax obligations for the period 2013–2015.

Despite the facts above, we are aware that there is a certain probability that a company from the group of non-fraud companies could report its economic operations opportunistically, but at the time of our study, companies were not convicted of such kind of activity, or they showed no signs of such activity. The sample of non-fraud companies is as close as possible to the sample of fraudulent companies regarding their SK NACE and their size as accounting units (micro, small, and large). We chose such a balanced sample or rather exactly matched to ensure the correct use of the tests of the model´s variables since the tests should be used for balanced samples.

The fraudulent companies (manipulators) were convicted of misleading financial reporting in connection with tax fraud in the years 2009–2018. Information on the companies was hand-collected, since there is no publicly accessible database in Slovakia in which companies identified as manipulators can be found. Obtaining the necessary information is difficult, which corresponds to the size of the sample of companies. The information comes from the Slovak media, if given facts were publicly shared or come from their own practice or common cooperation with accountants and auditors.

Beneish model

The Beneish model is a probabilistic model based on a probit regression method and indicates the perspectives concerning the tendency of companies for fraudulent accounting processes (Kramarova & Valaskova, 2020). For the purposes of the study, Beneish defined fraudulent financial reporting as an activity of earnings manipulation where management violates the GAAP in order to beneficially present a company´s financial performance (Beneish, 1999). The model was conceived on the sample of 74 U.S. companies that committed financial fraud in the years 1982–1992 and 2,332 companies that did not. The indicators were calculated from the financial reports starting in the year when a company was suspicious from reporting violating. The marginal value of the manipulation index (M-score) is -2.22. The score higher than -2.22 indicates a probability that the company applied opportunistic earnings management and misleading reporting. The classification performance of the model for different relative error cost ranges from 58% to 76% of manipulators correctly identified and 7.6% to 17.5% of non-manipulators incorrectly identified. (Beneish, 1999)

The indicators used in the model are of two characters — indicators pointing to aggressive accounting practices ($DSRI$, $DEPI$, $TATA$), and indicators pointing to the propensity to commit fraud (SGI, AQI, GMI, $SGAI$, $LVGI$) (Beneish, 1999). The M-score is calculated as follows:

$$\begin{gathered} M - score = -4.840 + 0.920 \cdot DSRI + 0.528 \cdot GMI + 0.404 \cdot AQI + \\ +0.892 \cdot SGI + 0{,}115 \cdot DEPI - 0.172 \cdot SGAI - 0.327 \cdot LVGI + \\ + 4.697 \cdot TATA \end{gathered} \tag{1}$$

where:

$DSRI$	–	Days Sales in Receivables Index
GMI	–	Gross Margin Index
AQI	–	Asset Quality Index
SGI	–	Sales Growth Index
$DEPI$	–	Depreciation Index
$SGAI$	–	Sales, General, and Administrative Expenses Index
$LVGI$	–	Leverage Index
$TATA$	–	Total Accruals to Total Assets

Variables of the model created in the conditions of the Slovak business environment

We used the same variables as Beneish did. In the process of calculations, we have approximated some input data following the content of the definition of the indicators in the source research paper, since the structure and the content of financial statements following the GAAP differ from the structure and the content of financial reports under the Slovak accounting standards.

Our model comprises 16 variables totally, since each indicator is calculated as two indexes (ex-post) with values in the year t (the year when a company was suspicious from fax fraud) and $t - 1$ (designation of the index is "tf"), and $t - 1$ and $t - 2$ (designation of the index is "b"). In the case of non-fraud companies, the designation of the variables is the same. We considered the same years as in the case of similar fraud companies according to their size and SK NACE classification, in other words, we matched the companies using the exact matching method, thus creating the sample of companies of the balanced nature.

Creating and validation of the model created in the conditions of the Slovak business environment

Using the discriminant analysis, the already mentioned 16 variables and counterfactual approach, we were able to quantify discriminant score — M-score$_{svk}$ accurately as possible so that the error of business classification into the group of fraudulent and into the group of non-fraud companies was as small as possible. If the score is positive, the model indicates opportunistic earnings management and the company´s tendency to tax liability avoidance. If the score reaches negative values, the model does not indicate tax fraud in the analysed period in the company under consideration.

A classification table containing the number and share of correctly and incorrectly classified companies from the training sample. At the same time, the correct classification of companies in which tax fraud occurred is more important for us, as the main goal of this study and the created model is to reveal this manipulation as accurately as possible.

Subsequently, to strengthen the correctness of the results, we applied bootstrapping to the training sample of 44 observations and obtained 2,000 observations. Bootstrapping was made with stratification of the companies based on their size, SK NACE classification, and based on tax fraud occurrence, i.e. we randomly generated the validation sample of 2,000 observations maintaining the share of the companies in the training sample. After that, we calculated the M-score$_{svk}$ also for the bootstrapped sample. The overall classification accuracy of our model is then expressed as the total share of correctly classified observations in this validation sample.

In general, the strength of this approach is that the gain results will be more reliable and credible because their validity is by bootstrapping verified on a much larger data sample. The significance and discriminant ability of M-score$_{svk}$ itself were verified based on the canonical correlation coefficient and its significance test.

We also compared the classification ability of our model with the classification ability of the original Beneish model. We hypothesize that the inclusion of more variables or more precisely, values of variables from the previous years will improve the classification accuracy of our model.

Application of the model created in the conditions of the Slovak business environment

We subsequently used the model in practice on an empirical data of 1,900 companies. The financial data on companies came from the Register of Financial Statements of the Ministry of Finance of the Slovak Republic, which is a publicly available database of financial reports. According to the principles of the discriminant analysis and the model itself, the companies were classified into the group of companies that probably violated accounting standards to avoid tax liabilities and into the group of companies that did not so. We also compared the results of this classification to the classification results of the Beneish model and analysed their detection match.

Results

As we have already mentioned, according to (Kramarova & Valaskova, 2020), fraudulent financial reporting is closely related to tax avoidance in Slovakia. According to the annuals reports of the Financial Administration of the Slovak Republic, which is the control body of the accounting and tax duties of companies in Slovakia, tax fraud on VAT and income tax have been a long-term key area. The quantitative aspects of the investigation of the Financial Administration in this area since 2009 are presented in Figure 1 in Annex. Based on the findings, we may deduce that fraudulent financial reporting and tax fraud are existing facts of the Slovak business environment. The value of findings e.g. in 2019 represented approx. 0.87% of the Slovak GDP in current prices for 2019 and approx. of 4.91% of the total value of earnings of the state budget of the same year. On the other hand, it is only a fraction of the identified entities involved in opportunistic earnings management, regardless of the exact specification of the reasons for this activity. It is, therefore, logical that the identification of these subjects in conditions of Slovakia has its justification.

Detection model of fraudulent companies

The discriminant function of our detection model is calculated as follows, with the threshold value equals 0.

$$\begin{gathered} M - score_{svk} = 0.29 \cdot AQI_b + 0.060 \cdot AQI_{tf} - 0.437 \cdot DEPI_b + \\ +0.180 \cdot DEPI_{tf} + 0.100 \cdot DSRI_b + 0.667 \cdot DSRI_{tf} + 0.943 \cdot GMI_b + \\ +1.511 \cdot GMI_{tf} - 1.561 \cdot LVGI_b - 1.523 \cdot LVGI_{tf} + 0.427 \cdot SGAI_b + \\ +0.681 \cdot SGAI_{tf} - 0.051 \cdot SGI_b + 1.920 \cdot SGI_{tf} + 0.497 \cdot TATA_b + \\ +1.031 \cdot TATA_{tf} - 3.699 \end{gathered} \tag{2}$$

If the M-score$_{svk}$ reaches positive values, the analysed company probably carried out opportunistic earnings management to avoid its tax liabilities in the given year. On the contrary, the negative values indicate that the company did not manage earnings opportunistically and should be classified as a non-fraud company.

The resulting function shows that the most important indicator by weight is SGI_{tf} calculated in the year, when the company was suspected in tax avoidance. Although growth per se does not imply manipulation, the existing studies point out the fact that growth companies are rather perceived as more likely than other companies to commit fraud by altering discretionary accounting accruals due to pressure exerted on managers to reach financial goals (e.g. Perols & Lougee, 2011; Ramirez-Orellana *et al.*, 2017) This index is followed by $LVGI_b$ and $LVGI_{ft}$ and according to e.g. (Beneish, 1999) changes in the leverage of the company are associated with the technical default of the company. On the other hand, the less important indicators by weight are $SGI_b$and AQI_{tf}. The AQI_{tf} in general expresses changes, and thereby risks, in the quality of the company's assets taking into account the ratio of non-current assets other than tangible assets (i.e. property, plant and equipment) to total assets.

A complete table of the model´s coefficients, together with an estimate of the coefficient bias, standard error and the confidence interval, determined by bootstrapping are presented in Table 3 in the Annex.

The significance and discriminant ability of M-score$_{svk}$ were verified based on the canonical correlation coefficient and its significance test. The results of the eigenvalues of the discriminant function are in Table 4. The value of the canonical correlation coefficient is 0.736 that indicates a sufficiently good detection ability of our model to distinguish fraudulent companies from non-fraud companies. According to the p-value of the test of the significance of the discriminant function (p-value = 0.047; Table 5 in the Annex), the model is statistically significant at the significance level of 0.05. The assumption of the equality of covariance matrices we verified using the Box test with the p-value of 0.137. The result is presented in Table 6.

Evaluation of classification ability of the model

The classification power, i.e. detection accuracy, of the model we verified by back-classifying the set of companies. The results are presented in Table 7 in the Annex.

According to the results (of both samples — training sample and validation sample), the model´s classification accuracy is very good, especially with a focus on the group of fraudulent companies, as the aim of this model should be to detect these fraudulent business practices as accurately as possible. The overall correct classification is 84.1%, which means that incorrectly classified companies as manipulators represented only 13.6% and incorrectly classified companies as non-fraud companies represented 18.2%. To strengthen the results, the validation sample of bootstrapped observations were also classified with the same overall success rate of 84.1%.

Discussion

In comparison to our model adapted to the conditions of the Slovak business environment, the Beneish model has lower performance in detecting companies that committed financial statement fraud to avoid own tax liability. In the case of the training sample, the Beneish model achieved 77.3% success rate of classification of non-fraud companies and 72.7% for fraudulent companies. Its overall classification accuracy is 75%. If we compare the results, the M-score$_{svk}$ achieves better classification results — overall by 9.1%, in the case of non-fraud companies by 4.2%, and by 13.7% in the case of fraudulent companies.

Based on the achieved results, we can generally confirm that the principle of classification of fraudulent companies using the Beneish model is justified and the variables used are relevant to the objective of the model. This is confirmed by studies by other authors, who used the variables of the original model to create a detection model characteristic of the country and the input data used. E.g. the results of the model by Ozkan (2018), who worked with the variables (not with the weights) of original Beneish model applied on companies listed on Borsa Istanbul, indicate that Beneish model is an appropriate tool in detecting companies that committed financial statement fraud. His model has an overall classification ability of 85.6%. The importance of the Beneish model in the conditions of the national economy, specifically when applied to small and medium companies in the Federation of Bosnia and Herzegovina, was also confirmed by Halilbegovic *et al*. (2020). In their study, they concluded that variables of Beneish model differed significantly between the tested groups and thereby they confirmed that variables could help detect fraudulent financial statements. Mano and Shehu (2017) have the same opinion, however, after the appropriate statistical operation, they modified the original Beneish model to the model of three variables, namely DSRI, GMI, and TATA. Other model created by Giunta *et al*. (2014) used the Beneish model's variables and created in conditions of Italian companies reduces the errors for false-positive at level 7.1% and correctly identifies the 92% of manipulating companies. Its overall classification capability was even higher than in the case of our model.

It follows from the above that the recalculation of the weights of variables (and therefore our approach) is considered relevant with regard to the information on fraudulent/non-fraud companies, while the initial designation (classification) of companies as fraud and non-fraud is based on the applicable accounting and tax legislation of the country.

The interesting results were also obtained from the test of the detection match of both models that we applied to the empirical data of 1,900 companies from the years 2016–2018. Table 8 presents the obtained results of companies´ classification into both groups by the Beneish M-score and by the M-score$_{svk}$, distinguishing between those companies that were classified equally with both models and those that were not. The Beneish model detected 743 (39.1%) companies as potential manipulators and the M-score$_{svk}$ 1,049 companies (55.2%). Both models matched in case of 621 companies that indicated as fraudulent, which is 32.7% of all cases. 1,157 (60.9%) companies the Beneish model marked as non-fraud companies and 851 (44.8%) marked the M-score$_{svk}$, which means that they identified 729 identical subjects, which is 38.4% of all cases. It follows from the above that the models did not agree on the identical classification only in the case of 28.9% of companies. This is a very useful result, as the application of both models reinforces the results obtained and the identical classification of the company into fraudulent indicates that in the company, the manipulation of earnings occurs with a high probability.

Regardless of relatively good results, we have to point out the main weakness of our study — the relatively small sample of companies that we could mark as manipulators. We have already stated the reason for this fact, however, on the other hand, this training sample is a relevant representative of companies that are engaged in earnings manipulation due to tax avoidance in Slovakia. We tried to eliminate this fact by exact matching of companies in the database and by bootstrapping the training sample to 2,000 observations, which strengthen the results, making them more precise. Another weakness of our study may be the fact that we linked earnings manipulation only with the issue of tax avoidance. However, we argue that there are no sources available in Slovakia that would provide information about fraudulent companies and at the same time the reason for such activities. Therefore, we relied on facts that were either mediated or obtained in connection with our activities in practice. It then follows that if a detection model for earnings manipulation is to be created, it is necessary to connect theoretical knowledge with real empirical data. As far as our model itself is concerned, it would also be appropriate to monitor companies over several years of their operation, which could bring more exact results and certainty in the process of detection of fraudulent companies. Regarding the use of our model on a sample of non-Slovak companies, the model is methodologically applicable. However, the fact that it is based on the strict identification of manipulators according to the Slovak accounting and tax legislation and financial statements prepared following Slovak accounting standards does not guarantee the correct identification of entities in other countries.

Conclusions

This study aimed to design a model that would be able to detect earnings manipulators (fraudulent companies) in the conditions of the Slovak business environment. We based on the principles of the discriminant analysis and identified the discriminant score of the detection model (M-score$_{svk}$) as accurately as possible. At the same time, we applied a similar approach as when creating propensity score models in counterfactual evaluations, where the model is created by including as many variables as possible, sometimes even interactions between variables, or powers of variables so that the propensity score is quantified for the unit as accurately as possible.

The result of our study is the model whose detection ability is more powerful than the detection ability of the Beneish model, which was the inspiration of our study. In the case of our study, we connected the issue of fraudulent financial reporting with the issue of tax avoidance, since we used financial reports of companies that were convicted of tax avoidance, however not all accounting irregularity is a signal for financial statement fraud.

The limit of our study is the functioning of the created model for companies located in other economies, as this model was created using real data on Slovak companies and accepting the structure and the content of financial reports following the Slovak accounting legislation. The detection ability of our model could be verified in other countries than Slovakia but it is necessary to determine the method of calculating the variables in the model, as in each country the methods of reporting financial indicators may differ significantly. In this, we see a possible further extension of this study. Moreover, we see the further direction of this study in verifying its results on a larger sample of companies.

References

Beatty, A. L., Ke, B., & Petroni, K. R. (2002). Earnings management to avoid earnings declines across publicly and privately held banks. *Accounting Review*, *77*(3).

Beaver, W. H., McNichols, M. F., & Nelson, K. K. (2007). An alternative interpretation of the discontinuity in earnings distributions. *Review of Accounting Studies*, *12*(4). doi: 10.1007/s11142-007-9053-0.

Beneish, M. D. (1999). The detection of earnings manipulation. *Financial Analysts Journal*, *55*(5).

Blazkova, I., & Dvoulety, O. (2019). Investigating the differences in entrepreneurial success through the firm-specific factors: microeconomic evidence from the Czech food industry. *Journal of Entrepreneurship in Emerging Economies*, *11*(2). doi: 10.1108/jeee-11-2017-0093.

Burgstahler, D., & Dichev, I. (1997). Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics*, *24*(1). doi: 10.1016/S0165-4101(97)00017-7

Callao, S., Jarne, J. I., & Wróblewski, D. (2017). Detecting earnings management investigation on different models measuring earnings management for emerging Eastern European countries. *International Journal of Research - Granthaalayah*, *5*(11). doi: 10.5281/ZENODO.1095448.

Cook, K. A., Huston, G. R., & Omer, T. C. (2008). Earnings management through effective tax rates: the effects of tax-planning investment and the sarbanes-Oxley Act of 2002. *Contemporary Accounting Research*, *25*(2). doi: 10.1506/car.25.2.6

Das, R. C., & Jena, S. K. (2016). Earnings management and equity issue firms: a study in Indian context. *Jindal Journal of Business Research*, *5*(1). doi: 10.1177/2278682116680926

Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting earnings management. *Accounting Review*, *70*(2).

Degeorge, F., Patel, J., & Zeckhauser, R. (1999). Earnings management to exceed thresholds. *Journal of Business*, *72*(1). doi: 10.1086/209601.

Dichev, I. D., & Skinner, D. J. (2002). Large–sample evidence on the debt covenant hypothesis. *Journal of Accounting Research*, *40*(4). doi: 10.1111/1475-679X.00083.

Durana, P., Valaskova, K., Vagner, L., Zadnanova, S., Podhorska, I., & Siekelova, A. (2020). Disclosure of strategic managers' factotum: behavioral incentives of innovative business. *International Journal of Financial Studies*, *8*(1). doi: 10.3390/ijfs8010017.

Francis, J., LaFond, R., Olsson, P., & Schipper, K. (2005). The market pricing of accruals quality. *Journal of Accounting and Economics*, *39*(2). doi: 10.1016/j.jacceco.2004.06.003.

Gill, J. D. (2004). *How to detect and prevent financial statement fraud*. Accociation of Certified Fraud Examiners.

Giunta, F., Bini, L., & Dainelli, F. (2014). Verifica della base informativa per l'analisi di bilancio: Le azioni di manipolazione contabile. *Controllo Di Gestione*, *2*.

Halilbegovic, S., Celebic, N., Cero, E., Buljubasic, E., & Mekic, A. (2020). Application of Beneish M-score model on small and medium enterprises in Federation of Bosnia and Herzegovina. *Eastern Journal of European Studies*, *11*(1).

Habib, A., & Hansen, J. C. (2008). Target shooting: review of earnings management around earnings benchmarks. *Journal of Accounting Literature*, *27*.

Homola, D., & Pasekova, M. (2020). Factors influencing true and fair view when preparing financial statements under IFRS: Evidence from the Czech Republic. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *15*(3). doi: 10.24136/eq.2020.026.

Hayn, C. (1995). The information content of losses. *Journal of Accounting and Economics*, *20*(2). doi: 10.1016/0165-4101(95)00397-2.

Healy, P. M. (1985). The effect of bonus schemes on accounting decisions. *Journal of Accounting and Economics*, *7*(1). doi: 10.1016/0165-4101(85)90029-1.

Healy, P. M., & Wahlen, J. M. (1998). A review of the earnings management literature and its implications for standard setting. *SSRN Scholarly Paper, 156445*. doi: 10.2139/ssrn.156445.

Irwandi, S. A., Ghozali, I., & Pamungkas, I. D. (2019). Detection fraudulent financial statement: Beneish M-score model. *WSEAS Transactions on Business and Economics*, *16*.

Jensen, M. C. (1993). The modern industrial revolution, exit, and the failure of internal control systems. *Journal of Finance*, *48*(3). doi: 10.1111/j.1540-6261.1993.tb04022.x.

Jones, J. J. (1991). Earnings management during import relief investigations. *Journal of Accounting Research*, *29*(2). doi: 10.2307/2491047.

Kaaya, I. D. (2015). The impact of international financial reporting standards (IFRS) on earnings management: a review of empirical evidence. *Journal of Finance and Accounting*, *3*(3). doi: 10.12691/jfa-3-3-3.

Kaplan, R. S. (1985). Evidence on the effect of bonus schemes on accounting procedure and accrual decisions. *Journal of Accounting and Economics*, *7*(1). doi: 10.1016/0165-4101(85)90030-8.

Kaya, C. T., & Turegun, N. (2017). Associations between earnings management manipulation types and debt contracts, political costs and characteristics of board of directors. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, *7*(2). doi: 10.6007/IJARAFMS/v7-i2/2995.

Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, *39*(1). doi: 10.1016/j.jacceco.2004.11.002.

Kovalova, E., & Frajtova Michalikova, K. (2020). The creative accounting in determining the bankruptcy of Business Corporation. *SHS Web of Conferences*, *74*, 01017. doi: 10.1051/shsconf/20207401017.

Kramarova, K., & Valaskova, K. (2020). Application of ohosen fraudulent detection technique in the Slovak business environment. *SHS Web of Conferences*, *74*, 01019. doi: 10.1051/shsconf/20207401019.

Leuz, C., Nanda, D., & Wysocki, P. D. (2003). Earnings management and investor protection: an international comparison. *Journal of Financial Economics*, *69*(3). doi: 10.1016/S0304-405X(03)00121-1.

Li, S. F., & Moore, E. A. (2011). Accrual based earnings management, real transactions manipulation and expectations management: U.S. and international evidence. Retrieved from http://www.jgbm.org/page/32%20Sherry%20Fang%20Li.pdf

Marinakis, P. (2011). An investigation of earnings management and earnings manipulation in the UK (Thesis (University of Nottingham only), University of Nottingham). Retrieved from http://eprints.nottingham.ac.uk/12874/.

Meek, G., & Thomas, W. (2003). A review of markets-based international accounting research. *Journal of International Accounting Research*, *3*. doi: 10.2139/ssrn.439143

Ozcan, A. (2018). The use of Beneish model in forensic accounting: evidence from Turkey. *Journal of Applied Economics and Business Research*, *8*(1).

Pasekova, M., Kramna, E., Svitákova, B., & Dolejsova, M. (2019). Relationship between legislation and accounting errors from the point of view of business representatives in the Czech Republic. *Oeconomia Copernicana*, *10*(1). doi: 10.24136/oc.2019.010.

Papik, M., & Papikova, L. (2020). Detection models for unintentional financial restatements. *Journal of Business Economics and Management*, *21*(1). doi: 10.3846/jbem.2019.10179.

Perols, J. L., & Lougee, B. A. (2011). The relation between earnings management and financial statement fraud. *Advances in Accounting*, *27*(1). doi: 10.1016/j.adiac.2010.10.004.

Podhorska, I., Siekelova, A., & Olah, J. (2019). Earnings analysis of SMEs: A case study in Slovakia. Retrieved from https://ibima.org/accepted-paper/earnings-analysis-of-smes-a-case-study-in-slovakia/.

Ramirez-Orellana, A., Martinez-Romero, M. J., & Marino-Garrido, T. (2017). Measuring fraud and earnings management by a case of study: evidence from an international family business. *European Journal of Family Business*, *7*(1). doi: 10.1016/j.ejfb.2017.10.001.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrics*, *70*(1). doi: 10.1093/biomet/70.1.41.

Rosenbaum, P. R., & Rubin, D. B. (1985). The bias due to incomplete matching. *Biometrics*, *41*(1). doi: 10.2307/2530647.

Sajnog, A. R. (2019). Executive compensation and comprehensive income: evidence from Polish listed companies. *Oeconomia Copernicana*, *10*(3). doi: 10.24136/oc.2019.024.

Sapar, N. R. (2008). Earnings management and performance of Indian equity rights issues. In *21st Australasian finance and banking conference 2008*. doi: 10.2139/ssrn.1155027.
Shuto, A. (2008). Earnings management to exceed the threshold: a comparative analysis of consolidated and parent-only earnings. *Journal of International Financial Management and Accounting*, *20*.
Stuart, E. A. (2010). Matching methods for causal inference: a review and a look forward. *Statistical Science*, *25*(1). doi: 10.1214/09-STS313.
Svabova, L., Valaskova, K., Durana, P., & Kliestik, T. (2020). Dependency analysis between various profit measures and corporate total assets for Visegrad group's business entities. *Organizacija*, *53*(1). doi: 10.2478/orga-2020-0006.
Swiderski, M., Goncharov, I., & Bissessur, S. (2010). Earnings management in central and Eastern Europe: the Czech, Hungarian and Polish cases. MSc in Accounting and Control (Dissertation thesis). Universiteit van Amsterdam, Amsterdam, Netherland.
Valaskova, K., & Durana, P. (2020). Global context of disparities in earnings management among enterprises: evidence from Slovakia. *SHS Web of Conferences, 74*, 01034. doi: 10.1051/shsconf/20207401034.
Van caneghem, T. (2002). Earnings management induced by cognitive reference points. *British Accounting Review*, *34*(2). doi: 10.1006/bare.2002.0190.
Wang, S., & Chen, S. (2012). The motivation for tax avoidance in earnings management. In *2012 international conference on engineering and business management*. Shanghai.
Weil, R. L., Schipper, K., & Francis, J. (2013). *Financial accounting: an introduction to concepts, methods and uses*. Cengage Learning.
Willey, K. M. (2019). *Stock market short-termism: law, regulation, and reform*. Springer.

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Annex

Table 1. Frequencies of companies based on their size as accounting units

Size	All		Non-fraud		Fraudulent	
	Frequency	%	Frequency	%	Frequency	%
large	6	13.6	3	13.6	3	13.6
micro	16	36.4	8	36.4	8	36.4
small	22	50.0	11	50.0	11	50.0
Total	44	100.0	22	100.0	22	100.0

Table 2. Frequencies of companies based on their SK NACE

SK NACE	All		Non-Fraud		Fraudulent	
	Frequency	%	Frequency	%	Frequency	%
F – Construction	6	13.6	3	13.6	3	13.6
G – Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	8	18.2	4	18.2	4	18.2
H – Transportation and Storage	10	22.7	5	22.7	5	22.7
I – Accommodation and Food Service Activities	6	13.6	3	13.6	3	13.6
L – Real Estate Activities	4	9.1	2	9.1	2	9.1
M – Professional, Scientific, and Technical Activities	4	9.1	2	9.1	2	9.1
N – Administrative and Support Service Activities	4	9.1	2	9.1	2	9.1
Q – Human Health and Social Work Activities	2	4.5	1	4.5	1	4.5
Total	44	100.0	22	100.0	22	100.0

Table 3. Coefficients of M-score$_{svk}$ for detecting companies involved in misleading financial reporting (fraudulent/non-fraud companies)

Canonical Discriminant Function Coefficients					
Variable	Coefficient	Bootstrap[a]			
		Bias	Std. Error	95% Confidence Interval	
				Lower	Upper
AQI_b	.290	.037	.367	-.349	1.086
AQI_tf	.060	-.002	.019	.035	.080
DEPI_b	-.437	.122	.391	-1.022	.519
DEPI_tf	.180	-.246	.676	-1.507	1.154

Table 3. Continued

Variable	Coefficient	Bootstrap[a]			
		Bias	Std. Error	95% Confidence Interval	
				Lower	Upper
DSRI_b	.100	-.013	.199	-.301	.451
DSRI_tf	.667	-.012	.440	-.090	1.412
GMI_b	.943	-.189	.532	-.677	1.351
GMI_tf	1.511	-.105	.629	-.171	2.414
LVGI_b	-1.561	-.001	.719	-2.592	-.001
LVGI_tf	-1.523	.004	.630	-2.567	-.319
SGAI_b	.427	.203	.465	-.039	1.669
SGAI_tf	.681	-.173	.460	-.937	1.144
SGI_b	-.051	.021	.271	-.560	.533
SGI_tf	1.920	.118	.896	.993	3.216
TATA_b	.497	.224	.777	-.483	2.540
TATA_tf	1.031	-.129	.755	-.967	2.165
(Constant)	-3.699	.233	1.605	-6.766	-.289

Canonical Discriminant Function Coefficients

Unstandardized coefficients

a. Unless otherwise noted. bootstrap results are based on 2,000 stratified bootstrap samples

Table 4. Eigenvalues of the discriminant model

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.180[a]	100.0	100.0	.736

a. First 1 canonical discriminant functions were used in the analysis.

Table 5. Wilks'test of statistical significance

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.459	26.503	16	.047

Table 6. Box's test of equality of covariance matrices of canonical discriminant function

Test Results		
Box's M		2,266
F	Approx.	2,213
	df1	1
	df2	5292,000
	Sig.	,137

Tests null hypothesis of equal population covariance matrices of canonical discriminant functions.

Table 7. Classification table of the M-score$_{svk}$ and Beneish model

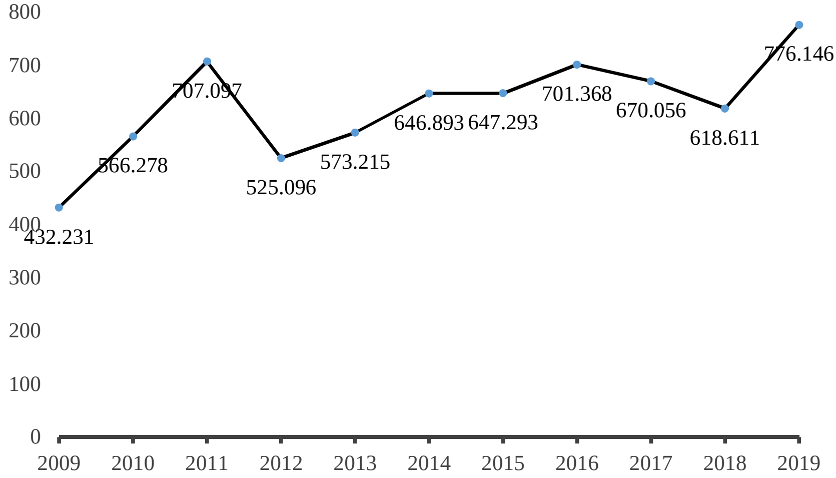
Classification Results[a]				
	Tax fraud reality	**M-score$_{svk}$**		**Total**
		Non-fraud	**Fraudulent**	
Count	Non-fraud	18	4	22
	Fraudulent	3	19	22
%	Non-fraud	81.8%	18.2%	100.0%
	Fraudulent	13.6%	86.4%	100.0%
Total	**M-score$_{svk}$**			**84.1%**
	Tax fraud reality	**Beneish model**		**Total**
		Non-fraud	**Fraudulent**	
Count	Non-fraud	17	5	22
	Fraudulent	6	16	22
%	Non-fraud	77.3%	22.7%	100.0%
	Fraudulent	27.3%	72.7%	100.0%
Total	**Beneish model**			**75.0%**

a. 84.1% of original grouped cases correctly classified.
For split file $bootstrap_split=0. 84.1% of original grouped cases correctly classified.[a]

Table 8. Detection match of the Beneish model and M-score$_{svk}$

Beneish_18 * class Cross tabulation					
			M-score$_{svk}$		**Total**
			Non-fraud	**Fraudulent**	
Beneish_18	Non-fraudulent	Count	729	428	1,157
	Fraudulent	Count	122	621	743
	Total	Count	851	1,049	1,900
		% of Total	44.8%	55.2%	100.0%

Figure 1. Total volume of findings, including cases of tax determined by devices (in thousands of EUR)



Source: own elaboration based on Annual Report of the Financial Report 2009–2019.