Beneish Model for the Detection of Tax Manipulation: Evidence from Slovakia[1]

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Abstract

To test the usefulness of the Beneish model, we use a unique, not publicly available database from the Financial Administration of the Slovak Republic, aggregating the results of all on-site financial inspections conducted by this authority during 2015 – 2019. This database is paired with firm-level accounting data from the Registry of Financial Statements and the Business Register to obtain additional corporate governance data. Our results indicate that (a) the performance of the Beneish model is inferior for the Slovak data; (b) there are several significant financial variables with statistical and economic significance, but their relevance is conditional on the industry group; and (c) corporate governance indicators appear to be more relevant preventive factors of fraudulent behavior, especially foreign ownership, female CEO and corporate social responsibility.

Keywords: *earnings manipulation, Beneish model, accounting fraud, Slovakia, corporate governance*

JEL Classification: D24, G30, L60, L80, M21

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Introduction

In this paper, we apply the well-known Beneish (1999) earnings manipulation model for detecting tax fraud utilizing a unique dataset of on-site financial controls performed by the Financial Administration of the Slovak Republic during the years 2015 – 2019. This dataset enables us to precisely differentiate between non-violators and violators, which is usually not possible in most empirical studies. Our results indicate that the Beneish model performs inferiorly in the Slovak business environment. Even though some of the firm-level variables are statistically significant, even in terms of the economic impact of their effect, the overall model performance is rather weak. We show that some corporate governance indicators, such as having a female CEO, corporate foreign ownership, and social responsibility to the firm's employees, play a more critical role. As such, searching for a better tool than Beneish model to detect tax manipulation in the Slovak Republic is still necessary.

Juggling corporate accounting and financial statements is an integral part of corporate finance. The act of intentionally influencing the process of financial reporting to obtain some gain is widely known as earnings management, which includes various motivations: from receiving higher bonuses, through avoidance of declining ratings, to, perhaps, most importantly, tax savings and boosting the value of the company – or just creating a positive impression of company stability. Some of the earnings management techniques are legal, and others are not. The latter techniques are the subject of our analysis, and we will refer to these illegal techniques as fraud or financial manipulation.

Accounting fraud represents a significant threat to the existence and efficiency of capital markets (Amiram et al., 2018) but also to the fiscal policy of the state (Slemrod, 2007). Financial manipulation reduces investors' confidence, making them less willing to participate in financial markets (Giannetti and Wang, 2016). The study of the manipulation of financial and accounting reporting has an interdisciplinary character (Uretsky, 1980), while the field of study is determined by the effects that are the subject of analysis. This is also reflected in a wide range of definitions, from which we will use the broadest. Rezaee (2002) defined financial manipulation as the intentional misstatement or omission of data in accounting and financial statements and the misuse of accounting standards, principles, and

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methods to deceive users, primarily investors, creditors, and the state. Creative accounting must be distinguished from financial manipulation, the perception of which is also significantly different, as reflected in a wide range of definitions (e.g., Amat, 2004).

Accounting and financial manipulation can improve one's results in the eyes of investors, shareholders, or creditors and reduce a firm's tax liability toward the state (Eilifsen et al., 1999; Noor et al., 2012). Some researchers have noted that the dominant elements of manipulation are not only income but also the overvaluation of property, the use of which results in tax benefits in the form of depreciation or direct costs for acquisition (Beasley et al., 1999; Badertscher et al., 2006), resulting in an advantage on both sides.

The overvaluation of a company's assets and income is related to the company's activity on the capital markets and the possible motivation of the management to present better results, thus following their interests connected with their remuneration. Many works have been devoted to researching this type of manipulation, of which we can highlight some of the most influential studies, e.g., Burns and Kedia (2006), Erickson et al. (2006), Johnson et al. (2009), Armstrong et al. (2010), Call et al. (2016). These works focus on finding relationships between possible internal and external causes (remuneration of management, manipulation of the market value of shares, acquisition of additional financial resources, etc.) and financial manipulation. In the second case, companies declare lower revenues or higher costs, reducing their tax liabilities to the state (Harris et al., 1993).

The manipulation techniques in both cases deviate from usual financial reporting patterns. Connecting tax and financial reporting could prevent such manipulation. Nevertheless, the partial separation of these systems allows for manipulation from which subjects have advantages, either in increasing the firm's value or reducing tax liability (Eilifsen et al., 1999). Sometimes manipulators can simultaneously achieve an advantage on both sides due to the partial separation of these systems (Frank et al., 2006). The primary outcome, stemming from separate financial and tax reporting, is manifested in the empirical research that the development of detection models cannot be unified and used indefinitely in the conditions of each system equally.

Another problem in the research area of detecting tax manipulation stems from the data available for such analysis; that is why a substantial part of attention has primarily focused on advanced economies (Shackelford and Shevlin, 2001). Naturally, constructing detection models in the conditions of less developed systems (from the perspective of data availability) is problematic (Perols et al., 2017). In such situations, models developed elsewhere are often applied in practice, leading to incorrect conclusions about the possible detection of tax manipulation or, in some cases, to unverifiable conclusions, primarily due to the size of the analyzed sample.

Finally, the last concern about tax fraud detection models is related to the problem that many manipulative firms are poorly categorized during the development of models because they were not explicitly revealed (Dechow et al., 2011). During the construction of prediction models, we usually work under the naive assumption that companies that have not been detected are so-called non-manipulators, which significantly distorts the results within these models. Therefore, detection models with high accuracy (approximately 80%) successfully detect manipulative firms in which authorities have detected manipulation (Persons, 1995). Thus, if the model is applied to the entire sample of companies in a given country, the results will likely be affected by either type I or type II errors.

To address the pitfalls mentioned above, this paper focuses on verifying a straightforward approach for detecting tax fraud – the Beneish (1999) model – in local conditions of companies operating in the Slovak Republic. Our main finding is that these models perform poorly, and their real-world application is not advised.[2]

1. Data and Methodology

We use a unique (not publicly available) database from the Financial Administration of the Slovak Republic that contains the results of all on-site financial inspections conducted by this authority during the years 2015 – 2019. This database is paired with (a) firm-level data obtained from the Register of Financial Statements (www.registeruz.sk), in which all Slovak firms are obliged to provide their balance sheets and income statements, and (b) Business Register (www.orsr.sk), from which we acquired additional firm-level information, such as the composition of management boards (or those acting in the name of the entity) and ownership structure. Our final sample comprises 4099 financial inspections, from which all the necessary firm-level data to apply the Beneish (1999) model are available for 2047 companies.[3]

[2] Our work was motivated by several studies that used the Beneish model for the identification of tax avoidance in the conditions of Slovak Republic. Most of these works supporting the validity and relevance of using the Beneish model in Slovakia have however been based on newspaper reports or personal experience, which would not qualify them as standard research sources. We present our results on a relevant and sufficiently large sample to show (in the spirit of the famous "theory of dead ends" by Jára Cimrman) that this is not the right way.

[3] Due to the proprietary character of our data, we cannot disclose additional details. However, identified violations during the inspections represent approximately 3/4 of our observations, homogenously across NACE groups.

Beneish (1999) used a weighted and unweighted probit model on a sample of 50 manipulators and 1,708 non-manipulators, matched from the population of the Compustat database. As is the case of the majority of such detection models, the main drawback of the Beneish model is that it has been estimated on a sample of US companies, using financial information for publicly traded companies almost a quarter of a century ago – thus, its relevance to Slovak enterprises may be questionable. By its construction, the application of the Beneish model requires the calculation of eight indicators (see Table A.1), all based on comparing two successive accounting periods to detect an unusual event. The final model takes the following form:

$$\begin{aligned}\text{M-score} &= -4.84 + 0.92 \times DSRI + 0.528 \times GMI + 0.404 \times AQI + 0.892 \times SGI + \\ &+0.115 \times DEPI - 0.172 \times SGAI + 4.679 \times TATA - 0.327 \times LVGI\end{aligned} \tag{1}$$

where

DSRI – days sales in receivable index;
GMI – gross margin index;
AQI – asset quality index; SGI – sales growth index;
DEPI – depreciation index;
SGAI – selling, general and administration expenses index;
LVGI – leverage index; TATA – total accruals to total assets index;
(for more details see Table A.1).

The construction of individual variables in the Beneish model follows the same structure, where a financial ratio for the current accounting period is divided by the same financial ratio for the previous accounting period. The indicators thus define rate-of-change indices, to detect sudden changes in sales dynamics (SGI), the composition of assets and liabilities (AQI, LVGI, and TATA), depreciation (DEPI), and the composition of sales (DSRI, GMI, SGAI). This model definition has both a benefit and a weakness. As the model captures changes, it is possible to identify the period during which manipulation may have occurred. On the other hand, the model fails to identify a continuous manipulation of financial statements, as the similar ongoing manipulation of consecutive statements would not introduce a detectable jump in the calculated indices.

An M-score of less than –2.2 indicates that the firm is not a manipulator, and an M-score greater than –2.2 signals otherwise. Similarly to the well-known Altman model used to detect financial distress, one might assume that the overall performance of such a model in local conditions would be relatively poor.

As our data are accurate in terms of discriminating exactly among manipulators and non-manipulators, we apply simple logistic regression to verify the applicability of this model in the conditions of Slovak companies:

$$P_j = E(Y_j \mid I_j) = \frac{1}{1+e^{-Z_j}} \tag{2}$$

where P_j denotes the fitted probability of firm *j* being found as in breach of tax regulations, Y_j is either 0 or 1, depending on whether the firm is actually in breach of regulations and I_j is the information set comprising the variables modeling the individual firm. For the original Beneish model, I_j includes the values of DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, and TATA, resulting in:

$$\begin{aligned} Z_j &= \beta_0 + \beta_1 DSRI_j + \beta_2 GMI_j + \beta_3 AQI_j + \beta_4 SGI_j + \beta_5 DEPI_j + \\ &+ \beta_6 SGAI_j + \beta_7 LVGI_j + \beta_8 TATA_j + \varepsilon_j \end{aligned} \tag{3}$$

where ε_j is the error term. The extended model (on which we further elaborate in Section 2.2) includes additional variables for the ratio of personal to total cost (personalToCosts) and two dummy variables to indicate whether there a foreign entity has a stake in the firm (stakeForeign) or has a woman in a managerial position or as a statutory of the firm (statWoman):

$$\begin{aligned} Z_j &= \beta_0 + \beta_1 DSRI_j + \beta_2 GMI_j + \beta_3 AQI_j + \beta_4 SGI_j + \beta_5 DEPI_j + \\ &+ \beta_6 SGAI_j + \beta_7 LVGI_j + \beta_8 TATA_j + \beta_9 stakeForeign_j + \\ &+ \beta_{10} statWoman_j + \beta_{11} personalToCosts_j + \varepsilon_j \end{aligned} \tag{4}$$

2. Results

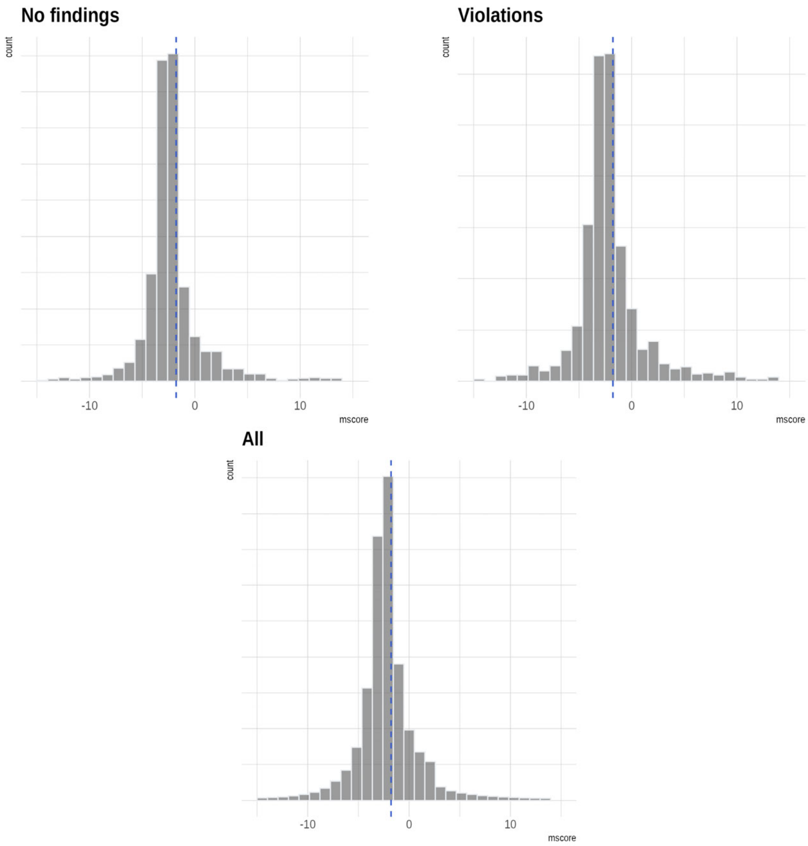
2.1. Performance of the Beneish Model in Slovak Conditions

First, we examine how the Beneish model works when applied naively, i.e., we take the estimated weights of given parameters and compute the M-scores. Recall that an M-score of less than –2.2 indicates that the firm is not a manipulator; an M-score greater than –2.2 signals otherwise.

Figure 1 captures these results for all inspected firms in our sample (both with no findings and those with confirmed violations) and the entire population of firms operating in Slovakia (data from the Register of Financial Statements of a total of 337,166 firms). We can see that the differences among confirmed violators, non-violators, and the entire sample of firms operating in Slovakia are negligible. Such a naïve application of the Beneish model does not make much sense in Slovak business conditions.

Figure 1

M-score Distribution (inspected firms and population)



Source: Own calculations.

We further proceed with estimating logistic regressions, including all Beneish indicators. The results are presented in four separate tables, as we differentiate between high-severity violations (over 26,600 EUR,[4] see Table 1), high-severity violations on a dataset cleaned for extreme values (Table 2), low-severity violations (over 2,660 EUR,[5] see Table 3) and low-severity violations on a cleaned dataset without extremes (Table 4).

[4] We derived the threshold for expressing higher severity from the Criminal Code, which sets a higher penalty rate for crimes above this threshold. It is the threshold defining the second highest severity in the Slovak criminal code.

[5] As in the previous case, this is a limit derived from the Criminal Code. We did not define the severity across all the boundaries defined in the criminal law since the initial crime threshold is set to only 266 EUR. We consider this to be a very low value in order to rule out accounting or other minor errors.

Overall, the performance of the Beneish model is inferior using the Slovak data. Only the asset quality index (AQI) helps significantly to differentiate between non-violators and violators. Furthermore, this holds for the NACE B-E group only. This group's total accruals to total asset (TATA) indicator serves as a preventive factor, with an odds ratio close to zero. In the case of low-severity violations, the sales growth index (SGI) is a significant risk factor for firms in the NACE A classification. A few other odds ratios are statistically significant but with values close to 1, indicating that the effect is relatively weak.

For the overall fit of our models, the pseudo-R^2 is approximately zero. However, the Pearson goodness-of-fit test indicates a good fit (the number of covariate patterns is not presented in the tables, but it is close to the number of observations, making the applicability of the Pearson chi^2 test questionable, although not necessarily inappropriate). Specificity, the ability of a model to correctly classify true negatives, is close to 100% in the case of high-severity violations. On the other hand, the sensitivity, i.e., correct classification of true positives, is below 10% on average. The situation is slightly different in low-severity violations; here, the specificity is approximately 80% on average, and the sensitivity is almost 30%. These characteristics are marginally better in models estimated on a sample without outliers. In addition, we computed the area under the ROC (Receiver Operating Characteristic) curve, for which an area of 50% indicates the model has no class separation capacity. Apart from one exception in minor violations (NACE A group), this is the case for our models – the area under the ROC curve is approximately 50 – 60%. In contrast, a good classification model should yield results above 80%.

2.2. Extending the Beneish Model

We follow the stream of literature that confirms that nonfinancial firm characteristics are important by extending our baseline model in several ways. We have included a variable for foreign ownership, as its impact is well documented in the corporate finance literature. Estrin et al. (2009) provide evidence of the positive role of foreign ownership caused not only by the provision of additional investments but also by micro-level management practices and corporate governance reforms. Furthermore, as noted in a survey by Baumöhl and Kočenda (2022), one of the most important factors for firm survival is the presence of a foreign owner (see also Baumöhl et al., 2019). Using a sample of German firms, Franco and Gelübcke (2015) show that in most cases, domestic firms suffer from higher competition introduced by foreign firms, except when they are part of a high-R&D region or a high-tech sector. Alfaro and Chen (2012) document higher resilience of multinational subsidiaries than local counterparts using worldwide data. Taymaz and Özler (2007) document that in the Turkish manufacturing industry, foreign plants have higher efficiency and survival probabilities only in the initial phases but not in the long term and that the benefits of foreign direct investment disappear when the industry and other factory characteristics are controlled for. Mata and Portugal (2004) provide evidence of sharp differences between small domestic and foreign firms regarding their entry and survival. In summary, a "foreign ownership" control variable should be included in every empirical work in the field of corporate finance (in our Tables, this variable is denoted as "stakeForeign," which takes a value of 1 if foreign ownership is present and is zero otherwise).

The second variable extending our baseline model is the gender of the CEO (denoted as "statWoman," a variable that takes a value of 1 if the CEO (or statutory) is a woman and is zero otherwise), which appears to be a relevant factor in explaining the propensity to engage in criminal activity, such as bribery (Dollar et al., 2001; Swamy et al., 2001). Hanousek et al. (2019) show that having a female CEO is detrimental to firm efficiency in high-corruption environments, and they explain that this could be due to factors such as higher risk aversion (Charness and Gneezy, 2012; Faccio et al., 2016), less overconfidence (Lundeberg et al., 1994; Barber and Odean, 2001), or that women have more pro-social attitudes than men (Eckel and Grossman, 1998; Funk and Gathmann, 2011).

Finally, our third variable ("personalToCosts") is the ratio of personal costs to total costs. The underlying idea behind this variable is as follows. There is an overlap between corporate social responsibility (CSR) and corporate governance (Jamali et al., 2008), as firms are held responsible not only to internal stakeholders but also to external stakeholders and society in general, and this holds especially concerning taxation (Huseynov and Klamm, 2012). As in Slovakia, there are no measurements of CSR; we utilized the ratio of personal costs to total costs. It is common in Slovakia to employ an employee as a self-employed worker for tax reasons. Hence, given the data available, we consider this variable a good proxy of CSR.

The results from extended models are presented in Columns (6) – (10) in Tables 1 – 4. For high-severity violations (Table 1), surprisingly, foreign ownership in the NACE B-E group does not help a firm be more honest with its accounting. On the other hand, NACE G-S does help, along with a female CEO. The ratio of personal costs to total costs is a significant preventive factor in NACE B-E and NACE F. Even if we clean the sample of outliers, the results remain essentially the same (Table 2).

Moving on to low-severity violations (Table 3), foreign ownership and female CEO are significant preventive factors for the NACE G-S group. Moreover, personal costs play an important role for NACE A and NACE B-E. Again, the results do not change after the elimination of extreme values.

T a b l e 1

Results for the Beneish Model – High-Severity Violations (over 26,600 EUR), Raw Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample	**NACE A**	**NACE B-E**	**NACE F**	**NACE G-S**	**Full sample**	**NACE A**	**NACE B-E**	**NACE F**	**NACE G-S**
stakeForeign						0.901	1.703	2.156**	1.504	0.621**
						(0.157)	(2.263)	(0.769)	(1.329)	(0.147)
statWoman						0.734**	0.669	0.932	1.409	0.622***
						(0.104)	(0.502)	(0.369)	(0.659)	(0.111)
personalToCosts						0.119***	1.996	0.00176***	0.0114**	0.366
						(0.0634)	(5.531)	(0.00302)	(0.0251)	(0.230)
DSRI	1.002*	0.991	0.987	0.994	1.002*	1.003**	0.999	0.980	0.992	1.003**
	(0.00109)	(0.170)	(0.0643)	(0.0104)	(0.00135)	(0.00111)	(0.166)	(0.0642)	(0.0122)	(0.00138)
GMI	1.001	1.079	1.001	0.971**	1.001	1.001	1.089	1.006	0.977*	1.001
	(0.000662)	(0.156)	(0.00923)	(0.0134)	(0.00101)	(0.000661)	(0.170)	(0.0130)	(0.0137)	(0.000988)
AQI	0.724	15.65	8.342**	0.221	0.531	0.731	13.31	5.334**	0.124	0.602
	(0.532)	(116.2)	(34.360)	(0.885)	(0.475)	(0.565)	(99.72)	(21.745)	(0.490)	(0.553)
SGI	1.000	1.378	0.948*	1.018*	1.000	1.000	1.373	0.940	1.014	1.000
	(0.000213)	(0.454)	(0.0267)	(0.0101)	(0.000260)	(0.000213)	(0.465)	(0.0373)	(0.0103)	(0.000260)
DEPI	1.002	0.619	0.993	1.338*	1.002	1.000	0.627	0.965	1.275	0.999
	(0.0146)	(0.312)	(0.124)	(0.222)	(0.0160)	(0.00275)	(0.314)	(0.118)	(0.214)	(0.0161)
SGAI	0.999*	1.094	0.906	1.006	0.999	0.999**	1.091	0.902	1.005	0.999*
	(0.000555)	(0.143)	(0.116)	(0.0109)	(0.000656)	(0.000556)	(0.139)	(0.127)	(0.0118)	(0.000663)
LVGI	1.011	0.753	1.078	1.263	1.011	1.007	0.819	1.254	1.253	1.010
	(0.0450)	(0.704)	(0.246)	(0.551)	(0.0461)	(0.0450)	(0.810)	(0.315)	(0.540)	(0.0450)
TATA	0.919	3.344	0.263**	1.001	0.938	0.916	2.928	0.265**	0.987	0.937
	(0.0527)	(6.260)	(0.170)	(0.592)	(0.0501)	(0.0554)	(5.568)	(0.174)	(0.583)	(0.0503)
Constant	0.381	0.0165	3.40e-05**	0.821	0.490	0.500	0.0168	8.99e-05**	2.051	0.549
	(0.280)	(0.120)	(0.000140)	(3.276)	(0.439)	(0.387)	(0.123)	(0.000368)	(8.091)	(0.505)
Observations	2047	98	320	216	1364	2047	98	320	216	1364
LR chi^2	14.05	6.93	27.19	9.70	11.34	38.99	7.32	49.28	15.22	25.71
(*p*-value)	0.0804	0.5445	0.0007	0.2867	0.1834	0.0001	0.7730	0.0000	0.1727	0.0072
Pseudo R^2	0.0065	0.0794	0.0809	0.0396	0.0080	0.0180	0.0839	0.1466	0.0621	0.0182
Sensitivity	1.10%	12.50%	8.57%	7.27%	1.38%	1.32%	12.50%	11.43%	9.09%	1.38%
Specificity	99.94%	100.00%	99.20%	96.89%	99.91%	99.87%	100.00%	96.40%	96.27%	99.91%
Correctly classified	77.97%	85.71%	79.38%	74.07%	78.96%	77.97%	85.71%	77.81%	74.07%	78.96%
Pearson chi^2	2045.19	94.54	300.17	215.13	1363.26	2049.83	92.89	278.97	209.20	1362.92
(*p*-value)	0.1655	0.1624	0.4864	0.2203	0.2328	0.1410	0.1536	0.7666	0.2624	0.2173
ROC curve	0.5254	0.5976	0.6271	0.6096	0.5333	0.5826	0.6463	0.7390	0.6554	0.5870

Notes: Coefficients are odds ratios. Robust standard errors are reported in parentheses beneath the regression coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Own calculations.

T a b l e 2
Results for the Beneish Model – High-Severity Violations (over 26,600 EUR), Trimmed Data at the 2nd and 98th Percentiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample	**NACE A**	**NACE B-E**	**NACE F**	**NACE G-S**	**Full sample**	**NACE A**	**NACE B-E**	**NACE F**	**NACE G-S**
stakeForeign						0.797	2.079	2.182**		0.505**
						(0.157)	(2.871)	(0.794)		(0.140)
statWoman						0.732**	0.473	1.093	0.906	0.650**
						(0.112)	(0.400)	(0.442)	(0.542)	(0.124)
personalToCosts						0.143***	18.75	0.00286***	0.0150*	0.453
						(0.0846)	(59.81)	(0.00505)	(0.0355)	(0.329)
DSRI	1.015	0.802	1.098	0.824*	1.036	1.012	0.804	1.065	0.825*	1.035
	(0.0222)	(0.201)	(0.0759)	(0.0848)	(0.0292)	(0.0223)	(0.202)	(0.0738)	(0.0820)	(0.0295)
GMI	1.011	1.006	1.098	0.947	1.016	1.012	1.013	1.141	0.944	1.018
	(0.0304)	(0.182)	(0.0984)	(0.0692)	(0.0402)	(0.0306)	(0.196)	(0.109)	(0.0697)	(0.0404)
AQI	1.340	77.982	1.083e+07*	0.00173	0.422	1.137	26.042	1.624e+07*	0.000823	0.472
	(1.973)	(1.061e+06)	(9.083e+07)	(0.00926)	(0.669)	(1.679)	(338.002)	(1.414e+08)	(0.00453)	(0.756)
SGI	1.036***	1.960	0.999	1.015	1.060***	1.028**	1.941	0.949	1.006	1.056***
	(0.0132)	(0.872)	(0.0774)	(0.0182)	(0.0214)	(0.0130)	(0.834)	(0.0849)	(0.0185)	(0.0216)
DEPI	1.029	1.168	0.872	1.606**	1.019	1.021	1.061	0.829	1.521*	1.008
	(0.0891)	(0.964)	(0.245)	(0.367)	(0.106)	(0.0876)	(0.922)	(0.235)	(0.348)	(0.104)
SGAI	1.062***	1.974*	0.468**	1.077	1.080***	1.065***	2.171**	0.514*	1.078	1.083***
	(0.0221)	(0.718)	(0.176)	(0.0509)	(0.0299)	(0.0222)	(0.818)	(0.183)	(0.0510)	(0.0307)
LVGI	1.047	0.909	1.074	1.851	1.078	1.042	1.124	1.134	1.795	1.073
	(0.148)	(0.851)	(0.374)	(0.880)	(0.190)	(0.147)	(1.164)	(0.398)	(0.857)	(0.189)
TATA	0.648*	10.10	0.332	1.106	0.657	0.614*	11.50	0.336	1.179	0.666
	(0.163)	(22.19)	(0.264)	(0.808)	(0.204)	(0.155)	(26.98)	(0.269)	(0.852)	(0.212)
Constant	0.150	7.44e-07	4.49e-08**	61.33	0.393	0.237	1.34e-06	5.15e-08*	212.9	0.448
	(0.221)	(1.01e-05)	(3.78e-07)	(326.6)	(0.623)	(0.351)	(1.73e-05)	(4.50e-07)	(1.172)	(0.720)
Observations	1787	90	281	187	1185	1787	90	281	182	1185
LR chi^2	23.64	7.39	16.10	15.32	23.81	42.12	8.69	33.95	18.66	36.70
(*p*-value)	0.0026	0.4949	0.0409	0.0533	0.0025	0.0000	0.6502	0.0004	0.0447	0.0001
Pseudo R^2	0.0127	0.0912	0.0543	0.0751	0.0198	0.0226	0.1072	0.1145	0.0927	0.0304
Sensitivity	2.07%	13.33%	4.84%	18.18%	4.10%	2.07%	13.33%	14.52%	18.18%	4.10%
Specificity	99.64%	100.00%	99.54%	99.30%	99.47%	99.50%	100.00%	97.72%	97.83%	99.47%
Correctly classified	78.57%	85.56%	78.65%	80.21%	79.83%	78.46%	85.56%	79.36%	78.57%	79.83%
Pearson chi^2	1783.86	86.77	269.33	194.01	1182.19	1784.69	82.90	251.54	178.77	1191.10
(*p*-value)	0.1707	0.1470	0.3810	0.1097	0.2421	0.1589	0.1782	0.6353	0.2037	0.1726
ROC curve	0.5756	0.6498	0.636	0.619	0.5864	0.5954	0.6907	0.7167	0.6604	0.6059

Notes: Coefficients are odds ratios. Robust standard errors are reported in parentheses beneath the regression coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: Own calculations.

T a b l e 3

Results for the Beneish Model – Low-Severity Violations (over 2,660 EUR), Raw Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample	**NACE A**	**NACE B-E**	**NACE F**	**NACE G-S**	**Full sample**	**NACE A**	**NACE B-E**	**NACE F**	**NACE G-S**
stakeForeign						0.666***	0.619	1.064	1.704	0.556***
						(0.0970)	(0.803)	(0.329)	(1.366)	(0.102)
statWoman						0.654***	2.040	0.903	0.735	0.562***
						(0.0738)	(1.196)	(0.282)	(0.303)	(0.0776)
personalToCosts						0.309***	0.00217**	0.0224***	0.573	0.754
						(0.122)	(0.00520)	(0.0248)	(0.833)	(0.360)
DSRI	1.000	0.808	1.021	0.986	1.000	1.000	0.807	1.008	0.985	1.000
	(0.000617)	(0.149)	(0.0341)	(0.0107)	(0.000638)	(0.000642)	(0.158)	(0.0342)	(0.0113)	(0.000657)
GMI	1.001	0.842	0.993*	0.988	1.002	1.000	0.838	0.993*	0.989	1.002
	(0.000568)	(0.130)	(0.00358)	(0.0124)	(0.00150)	(0.000553)	(0.142)	(0.00341)	(0.0126)	(0.00151)
AQI	0.735	4.450	145.9**	0.619	0.519	0.776	16.58	87.20*	0.339	0.602
	(0.432)	(25.00)	(356.6)	(2.293)	(0.355)	(0.467)	(99.37)	(216.8)	(1.292)	(0.420)
SGI	1.000	5.941**	0.988	1.011	1.000	1.000	9.100**	0.988	1.011	1.000
	(0.000154)	(4.790)	(0.00790)	(0.00978)	(0.000342)	(0.000152)	(8.063)	(0.00770)	(0.00994)	(0.000343)
DEPI	1.006	0.911	1.274	1.165	1.004	1.003	0.887	1.286	1.177	1.001
	(0.0125)	(0.250)	(0.210)	(0.189)	(0.0135)	(0.0125)	(0.439)	(0.237)	(0.192)	(0.0135)
SGAI	1.000	1.426	0.963	1.017	1.000	1.000	1.325	0.985	1.019	1.000
	(0.000339)	(0.426)	(0.0475)	(0.0136)	(0.000348)	(0.000344)	(0.357)	(0.0496)	(0.0144)	(0.000354)
LVGI	1.045	1.066	0.702	0.903	1.105	1.044	0.830	0.733	0.913	1.099
	(0.0520)	(0.639)	(0.156)	(0.361)	(0.0894)	(0.0539)	(0.517)	(0.184)	(0.365)	(0.0856)
TATA	0.925	4.838	0.297***	0.632	0.976	0.924	3.992	0.266***	0.604	0.983
	(0.0624)	(7.037)	(0.138)	(0.321)	(0.0566)	(0.0650)	(6.176)	(0.133)	(0.310)	(0.0564)
Constant	1.090	0.0461	0.00573**	1.331	1.409	1.340	0.0227	0.0154*	2.537	1.522
	(0.641)	(0.261)	(0.0137)	(4.931)	(0.966)	(0.809)	(0.136)	(0.0374)	(9.665)	(1.066)
Observations	2047	98	320	216	1364	2047	98	320	216	1364
LR chi^2	8.03	22.23	23.28	7.63	10.58	40.53	30.01	37.30	8.87	37.47
(*p*-value)	0.4306	0.0045	0.0030	0.4700	0.2265	0.0000	0.0016	0.0001	0.6634	0.0001
Pseudo R^2	0.0028	0.1648	0.0531	0.0255	0.0056	0.0143	0.2226	0.0852	0.0297	0.0199
Sensitivity	2.55%	70.37%	23.02%	37.14%	4.21%	43.27%	81.48%	41.73%	40.95%	36.47%
Specificity	98.55%	63.64%	86.74%	75.68%	97.99%	65.13%	75.00%	76.24%	70.27%	75.90%
Correctly classified	54.32%	67.35%	59.06%	56.94%	55.57%	55.06%	78.57%	61.25%	56.02%	58.06%
Pearson chi^2	2044.41	93.22	313.92	214.73	1359.75	2045.63	103.57	312.50	214.90	1358.17
(*p*-value)	0.1685	0.1865	0.2786	0.2259	0.2538	0.1561	0.0393	0.2571	0.1816	0.2449
ROC curve	0.5222	0.7441	0.6096	0.5796	0.5351	0.5772	0.8140	0.6666	0.6074	0.5840

Notes: Coefficients are odds ratios. Robust standard errors are reported in parentheses beneath the regression coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: Own calculations.

T a b l e 4

Results for the Beneish Model – Low-Severity Violations (over 2,660 EUR), Trimmed Data at the 2nd and 98th Percentiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample	**NACE A**	**NACE B-E**	**NACE F**	**NACE G-S**	**Full sample**	**NACE A**	**NACE B-E**	**NACE F**	**NACE G-S**
stakeForeign						0.683**	0.626	1.195	0.700	0.567***
						(0.108)	(0.816)	(0.388)	(0.653)	(0.113)
statWoman						0.646***	1.910	1.056	0.647	0.545***
						(0.0784)	(1.147)	(0.344)	(0.306)	(0.0818)
personalToCosts						0.246***	0.00309**	0.0251***	0.957	0.483
						(0.111)	(0.00771)	(0.0295)	(1.477)	(0.278)
DSRI	1.005	0.800	1.002	0.836**	1.055**	1.001	0.807	0.974	0.832**	1.056**
	(0.0195)	(0.157)	(0.0596)	(0.0658)	(0.0283)	(0.0195)	(0.162)	(0.0603)	(0.0656)	(0.0286)
GMI	0.973	0.845	1.071	0.993	0.952	0.975	0.840	1.107	0.993	0.953
	(0.0247)	(0.130)	(0.0748)	(0.0612)	(0.0318)	(0.0248)	(0.143)	(0.0843)	(0.0612)	(0.0321)
AQI	0.573	6.863	8.690e+06**	0.126	0.0995*	0.505	18.47	6.274e+06**	0.0803	0.101
	(0.675)	(39.89)	(6.165e+07)	(0.652)	(0.139)	(0.601)	(112.6)	(4.470e+07)	(0.410)	(0.143)
SGI	1.022*	5.908**	1.072	0.998	1.050**	1.014	8.682**	1.033	0.997	1.043*
	(0.0131)	(4.878)	(0.0757)	(0.0170)	(0.0235)	(0.0128)	(7.811)	(0.0697)	(0.0174)	(0.0229)
DEPI	1.138*	0.640	1.163	1.140	1.188**	1.128	0.762	1.147	1.128	1.174*
	(0.0835)	(0.411)	(0.262)	(0.244)	(0.103)	(0.0834)	(0.551)	(0.263)	(0.243)	(0.103)
SGAI	1.025	1.454	0.966	1.044	1.033	1.028	1.324	1.001	1.053	1.034
	(0.0206)	(0.444)	(0.108)	(0.0450)	(0.0285)	(0.0207)	(0.420)	(0.112)	(0.0466)	(0.0291)
LVGI	1.096	1.075	0.877	1.317	1.215	1.090	0.841	0.905	1.298	1.214
	(0.134)	(0.644)	(0.271)	(0.586)	(0.190)	(0.134)	(0.526)	(0.280)	(0.581)	(0.193)
TATA	0.762	4.774	0.288*	0.769	0.929	0.734	3.835	0.268*	0.744	0.942
	(0.160)	(7.035)	(0.190)	(0.464)	(0.242)	(0.157)	(6.038)	(0.183)	(0.452)	(0.251)
Constant	1.050	0.0432	7.22e-08**	5.841	4.451	1.614	0.0240	1.62e-07**	9.995	5.804
	(1.239)	(0.254)	(5.14e-07)	(30.13)	(6.221)	(1.931)	(0.146)	(1.16e-06)	(51.04)	(8.239)
Observations	1787	90	281	187	1185	1787	90	281	187	1185
LR chi^2	13.64	13.98	15.07	10.9	24.92	43.45	19.96	26.35	11.88	50.31
(*p*-value)	0.0916	0.0822	0.0578	0.2073	0.0016	0.0000	0.0459	0.0057	0.3725	0.0000
Pseudo R^2	0.0055	0.1124	0.0392	0.0421	0.0153	0.0177	0.1605	0.0685	0.0459	0.0310
Sensitivity	12.80%	75.00%	19.67%	58.89%	16.92%	31.68%	79.17%	38.52%	58.89%	28.85%
Specificity	92.26%	64.29%	82.39%	54.64%	90.68%	80.35%	73.81%	74.21%	49.48%	86.32%
Correctly classified	56.46%	70.00%	55.16%	56.68%	58.31%	58.42%	76.67%	58.72%	54.01%	61.10%
Pearson chi^2	1788.36	95.08	275.94	185.67	1186.2	1786.60	103.51	277.18	185.45	1182.59
(*p*-value)	0.1524	0.0500	0.2795	0.2097	0.2172	0.1513	0.0089	0.2217	0.1693	0.2206
ROC curve	0.5456	0.7262	0.5964	0.6077	0.5789	0.5856	0.7793	0.6609	0.6219	0.6049

Notes: Coefficients are odds ratios. Robust standard errors are reported in parentheses beneath the regression coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: Own calculations.

3. Concluding Remarks

Apart from the Beneish model, we experimented with the Noor et al. (2012) model, but the results were not more meaningful. For example, the area under the ROC curve is always lower than 80%.[6] Interestingly, our nonfinancial indicators remain significant, even in this model. Future research on data from the Slovak Republic should thus be aimed in this direction and toward more modern approaches utilized within the machine learning stream of literature. Our results indicate that it is not advisable, particularly from a practical perspective, to rely on refurbished historical models from abroad that aspire to be universal, fit-all-data models. If nothing else, there are notable differences among the NACE groups.

We also believe that the possible construction of models should not be derived from comparing changes over time within a specific company. As a rule, companies that commit tax fraud do so systematically. Thus, such practices become part of their standard business practice, making it impossible to detect changes in behavior over consecutive periods. Furthermore, if a company moves from the regime of lawful conduct to tax fraud, this change usually occurs gradually. Additionally, we found a linearization of tax obligations in our conditions when analyzing the basic descriptive statistics and other indicators. Therefore, companies try to maintain a certain level of taxation, i.e., when revenues grow, their tax burden increases proportionally. However, this should not hold in the context of the theory of economies of scale, as further revenue growth should also be reflected in a higher marginal taxed economic result (the difference between revenues and costs).

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[6] To preserve space, these results are available upon request. The Noor et al. (2012) model is based on a sample of 73 companies subjected to tax investigation from 2001 to 2005. Six financial ratios were identified as predictive of companies' tax evasion: Working Capital (divided by total assets), Sales (divided by total assets), Debt (divided by total assets), Effective Tax Rate (tax paid divided by net profit), Inventories (inventories divided by sales), Account Receivables (receivables divided by total sales).

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Appendix

Table A.1
Beneish Model Indicators

Indicator	Formula	Slovak equivalents
DSRI	$\dfrac{\text{Receivables}_t / \text{Sales}_t}{\text{Receivables}_{t-1} / \text{Sales}_{t-1}}$	$\dfrac{\text{Pohľadávky}_t\ [41 + 53\text{ S Netto2}] / \text{Tržby}_t\ [03 + 04 + 05\text{ V1}]}{\text{Pohľadávky}_{t-1}\ [41 + 53\text{ S Netto3}] / \text{Tržby}_{t-1}\ [03 + 04 + 05\text{ V2}]}$
GMI	$\dfrac{(\text{Sales}_{t-1} - \text{Cost of goods sold}_{t-1})/\text{Sales}_{t-1}}{(\text{Sales}_t - \text{Cost of goods sold}_t)/\text{Sales}_t}$	$\dfrac{(\text{Tržby}_{t-1}\ [03 + 04 + 05\text{ V2}] - \text{Náklady predaného tovaru a služieb}_{t-1}\ [11 + 12 + 15\text{ V2}]) / \text{Tržby}_{t-1}\ [03 + 04 + 05\text{ V2}]}{(\text{Tržby}_t\ [03 + 04 + 05\text{ V1}] - \text{Náklady predaného tovaru a služieb}_t\ [11 + 12 + 15\text{ V1}]) / \text{Tržby}_t\ [03 + 04 + 05\text{ V1}]}$
AQI	$\dfrac{1 - (\text{Current assets}_t + \text{PP\&E}_t)/\text{Total Assets}_t}{1 - (\text{Current assets}_{t-1} + \text{PP\&E}_{t-1})/\text{Total Assets}_{t-1}}$	$\dfrac{1 - (\text{Obežný majetok}_t\ [33\text{ S Netto2}] + \text{DHM}_t\ [11\text{ S Netto2}] + \text{Časové rozlíšenie}_t\ [74\text{ S Netto2}] / \text{Celkové aktíva}_t\ [01\text{ S Netto2}]}{1 - (\text{Obežný majetok}_{t-1}\ [33\text{ S Netto3}] + \text{DHM}_{t-1}\ [11\text{ S Netto3}] + \text{Časové rozlíšenie}_{t-1}\ [74\text{ S Netto3}] / \text{Celkové aktíva}_{t-1}\ [01\text{ S Netto3}]}$
SGI	$\dfrac{\text{Sales}_t}{\text{Sales}_{t-1}}$	$\dfrac{\text{Tržby}_t\ [03 + 04 + 05\text{ V1}]}{\text{Tržby}_{t-1}\ [03 + 04 + 05\text{ V2}]}$
DEPI	$\dfrac{\text{Depreciation}_{t-1} / (\text{Depreciation}_{t-1} + \text{PP\&E}_{t-1})}{\text{Depreciation}_t / (\text{Depreciation}_t + \text{PP\&E}_t)}$	$\dfrac{\text{Odpisy}_{t-1}\ [22\text{ V2}] / (\text{Odpisy}_{t-1}\ [22\text{ V2}] + \text{DHM}_{t-1}\ [11\text{ S Netto3}])}{\text{Odpisy}_t\ [22\text{ V1}] / (\text{Odpisy}_t\ [22\text{ V1}] + \text{DHM}_t\ [11\text{ S Netto2}])}$
SGAI	$\dfrac{\text{Sales, general, and administrative expense}_t / \text{Sales}_t}{\text{Sales, general, and administrative expense}_{t-1} / \text{Sales}_{t-1}}$	$\dfrac{\text{Služby}_t\ [14\text{ V1}] / \text{Tržby}_t\ [03 + 04 + 05\text{ V1}]}{\text{Služby}_{t-1}\ [14\text{ V2}] / \text{Tržby}_{t-1}\ [03 + 04 + 05\text{ V2}]}$
LVGI	$\dfrac{(\text{LTD}_t + \text{Current Liabilities}_t) / \text{Total assets}_t}{(\text{LTD}_{t-1} + \text{Current Liabilities}_{t-1}) / \text{Total assets}_{t-1}}$	$\dfrac{(\text{Dlhodobé záväzky}_t\ [102\text{ S4}] + \text{Dlhodobé bankové úvery}_t\ [121\text{ S4}] + \text{Krátkodobé záväzky}_t\ [122\text{ S4}] + \text{Krátkodobé bankové úvery}_t\ [139\text{ S4}]) / \text{Celkové aktíva}_t\ [01\text{ S Netto2}]}{(\text{Dlhodobé záväzky}_{t-1}\ [102\text{ S5}] + \text{Dlhodobé bankové úvery}_{t-1}\ [121\text{ S5}] + \text{Krátkodobé záväzky}_{t-1}\ [122\text{ S5}] + \text{Krátkodobé bankové úvery}_{t-1}\ [139\text{ S5}]) / \text{Celkové aktíva}_{t-1}\ [01\text{ S Netto3}]}$
TATA	$\dfrac{\Delta\text{Current assets}_t - \Delta\text{Cash}_t - (\Delta\text{Current liabilities}_t - \Delta\text{Current maturities of LTD}_t - \Delta\text{Income tax payable}_t) - \text{Depreciation and amortization}_t}{\text{Total assets}_t}$	$\dfrac{\Delta\text{Obežný majetok}_t\ [33\text{ S Netto2} - 33\text{ S Netto 3}] - \Delta\text{Finančné účty}_t\ [71\text{ S Netto2} - 71\text{ S Netto3}] - (\Delta\text{Krátkodobé záväzky}_t\ [122\text{ S 4} - 122\text{ S 5}] + \Delta\text{Splatné dane}_t\ [57\text{ V1} - 57\text{ V2}]) - \text{Odpisy}_t\ [22\text{ V1}]}{\text{Celkové aktíva}_t\ [01\text{ S Netto2}]}$

Notes: Days sales in receivable index (DSRI), Gross margin index (GMI), Asset quality index (AQI), Sales growth index (SGI), Depreciation index (DEPI), Selling, general and administrative expenses index (SGAI), Leverage index (LVGI), Total accruals to total assets index (TATA).

Source: Own calculations.