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FISCAL AND ACCOUNTING FRAUD RISK DETECTION USING BENEISH MODEL. A ROMANIAN CASE STUDY

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ABSTRACT

The manipulation of the accounting and fiscal information is currently a much debated reality that occurs throughout economies and societies all over the world. The main purpose of this paper is focused on shaping and obtaining a model that can detect fraud/tax evasion risk, that could be useful both to fiscal authorities as part of the risk assessment analysis regarding the taxpayer behavior, and to auditors and even to entities from the private sector in the due diligence phase, when selecting potential business partners. The study focuses on regional data from the North-Eastern part of Romania. The main finding is that such a model should include financial, fiscal and nonfinancial variables.

Keywords: Beneish Model, Fraud/Tax Evasion Risk, Information Manipulation, Romania.

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1. INTRODUCTION

It can be stated that fraud and tax evasion are much debated subject matters that were treated in many works, both in the field of accounting and taxation as well as in the branch of law, as they are issues that pose global challenges. In Romania, in the recent years, the prevention and control of tax evasion and tax fraud have been declared a national priority at the level of the security and justice department, as these phenomena have widely spread, endangering the socio-economic development of the country.

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As per latest official figures (Romanian National Fiscal Council, 2013), tax evasion in Romania amounted at 16.2% of GDP in 2013, from which 75% was generated from VAT. In what concerns the European official data, the VAT gap (that can be considered as a proxy measure for tax evasion) also reached very high values, Romania being the EU Member State with highest VAT gap: 35.88 % of VAT Total Tax Liability (the amount that should have been collected) in 2016, 37.18% in 2015, and a 42.85% in 2014 (Directorate General Taxation and Customs Union, 2017). In order to fight against these harmful phenomena, it is necessary first to detect and analyze the most vulnerable economical areas in which they manifest. In this context, developing a model that could detect or predict fraudulent behavior among economic entities could be useful both to state authorities, as well as to the private business sector.

As a first step in analyzing financial ratios that could have major impact as variables in a detection model of fraud and tax evasion, this research article will present a case study carried out in the North-Eastern region of Romania that has as a main objective testing the possibility of detecting tax evasion risk by the application of the model developed by professor Beneish (1999) for detecting financial statement fraud, and as a secondary objective, testing whether there exists a connection between financial statement fraud risk and evading taxes risk through the methods incriminated as tax evasion. Also, a third objective is to develop a model useful in classifying economic entities in tax evaders and non-evaders, based on professor Beneish’s proposed indices, by means of statistical tools, using the discriminant analysis in IBM SPSS Statistics software.

The study focuses on this particular geographical area due to data resources and availability, taking also into account the fact that there are significant economic development differences between the analyzed region and other geographical parts of the country, this region being less developed and thus, more exposed to tax fraud crimes. In order to support the reasoning, we would like to mention the fact that research studies regarding the level of economic development and tax evasion (Schneider, Buehn, & Montenegro, 2010) concluded that underdeveloped countries have a larger underground economy.

In this regard in the following sections, the research methodology will be described in detail, as well as, the results and the conclusions, emphasizing limits, obstructions and future research directions.

2. LITERATURE REVIEW

The relationship between accounting and taxation has been analyzed in many studies from the relevant literature (Ristea, 2003; Bunget & Dumitrescu, 2008; Paliu-Popa & Ecobici, 2007; Fekete, Cuzdriorean, Sucală, & Matiş, 2009), that characterized it in the following manner: there is a dichotomy between accounting and taxation, the two being connected in some ways and disconnected in others; convergence and divergence, tolerance and intolerance coexist between accounting and taxation; accounting is influenced by taxation; it cannot be established a dominance of one or the other, as they are interdependent.

In our opinion, the relationship between accounting and taxation is a concurring one, thus, through logical construction it can be argued that an instrument useful for detecting financial and accounting fraud can also be effective for detecting fiscal fraud that is the indication for the manifestation of the tax evasion risk.

On the one hand, in what concerns the estimation and detection of fraud risk, in the specialized literature this subject was intensely debated, the main methods/ means/ models proposed being: obtaining econometrical models by use of logistical regression analysis (Spathis, Doumpos, & Zopounidis, 2002; Liou, 2008; Lenard & Alam, 2010); using analytical procedures (trend analysis, financial ratio analysis, reasonability tests and regression analysis) (Lee & Colbert, 1997); using agent-based modelling (Hashimzade, Myles, Page, & Rayben, 2015), neural networks (Fischthal, 1998), forensic accounting tools (Mekic, Halilbegovic, & Huri, 2017), or bank credit (Artavanis, Morse, & Tsoutsoura, 2015); using discriminant analysis in detecting accounting result manipulations (Dikmen & Kucukkocaoglu, 2009), etc.

On the other hand, in what concerns the detection of tax evasion risk there are not so many studies conducted, those identified being mainly focused on detecting tax evasion in the field of indirect taxes – that is the value added tax (Gupta & Nagadevara, 2007; Wu, Ou, Lin, Chang, & Yen, 2012).

3. RESEARCH METHODOLOGY

In the following sections, a series of variables will be analyzed – indices for detecting accounting manipulations proposed by Beneish in order to classify the entities in two categories: manipulators and non-manipulators – computed on the basis of financial statement indicators (balance sheet, profit and loss account and informative data) of the entities included in the analyzed sample. This sample is made out of entities that present tax evasion risk, from the North-Eastern region of Romania, identified by the current pending penal proceedings regarding tax evasion crimes.

The research methodology involves going through the following steps:

Step one – Extracting information from the central databases of the Ministry of Public Finances regarding the main indicators from the financial statements;
Step two – Extracting from the selected entities' financial statements the necessary parameters for computing the indices proposed by Beneish;
Step three – Computing, in the software Microsoft Excel the variables of the model;
Step four – Determining, based on the computed indices the *M-score*, according to Beneish equation;
Step five – Classifying the entities, depending on the obtained score, in one of the two categories: with fraud risk and without fraud risk;
Step six – Executing in the statistical analysis software SPSS 19.0 the discriminant analysis of the resulting computed indices in order to generate a discriminant function useful for detecting tax evading firms and interpreting the results;
Step seven – Conducting a confidence test in the results obtained by use of statistical analysis software SPSS 19.0;
Step eight – Presenting the results of the quantitative research, the conclusions and the future research possibilities.

4. IDENTIFYING FRAUD/ TAX EVASION RISK USING BENEISH MODEL

For the purpose of this study we chose to apply the model developed by professor Beneish (1999) to discover fraud in financial statements, as this is part of a bigger research that has as a final goal identifying the financial ratios that could have significant impact on tax evasion and as a main purpose developing a model for detecting tax evasion.

The Beneish model (Beneish 1999) is a mathematical model created by Professor Messod Daniel Beneish, designed to identify a series of financial rates indexes that can detect accounting fraud or the tendency of using manipulation techniques of the financial information. According to some opinions by Mehta and Bhavani (2017), Beneish M-score is similar to the Altman Z-score model, but it concentrates on the evaluation of the profit control level, while the Z-score model tracks the stage when an economic entity declares bankruptcy and finds its use, according to the identified research studies in the detection of financial fraud.

The model`s variables are built on data from the financial statements of the economic entities and once calculated, create a M-score that indicates the probability of using manipulative techniques of accounting data and information.

Various researchers have tested the efficiency of the model. In this respect (Mahama, 2015) applied the model on the Enron Corporation and concluded that the entity had been using techniques for manipulating accountancy data and information since 1997, long before declaring bankruptcy in 2001.

Moreover, other more recent studies are built starting from and on complementary grounds to the M-score model (Dechow, Ge, Larson, & Sloan, 2011; Vladu, Amat, & Cuzdriorean, 2017). Omar, Koya, Sanusi, and Shafie, (2014), who applied both the Beneish M-score model and financial ratios analysis, concluded that the Megan Media Holdings Berhad holding has manipulated its financial statements.

Other recent applications of the model can be found in research studies on the banking sector (Nyakarimi, Kariuki, & Kariuki, 2020), financial firms (Erdoğan & Erdoğan, 2020), on international companies from metals and mining sector (Volkov, 2020), on small and medium enterprises (Halilbegovic, Celebic, Cero, Buljubasic, & Mekic, 2020), etc.

In addition, a study conducted by MacCarthy (2017) stated that the Beneish M-score model is effective in detecting fraudulent techniques and should be used together with the Altman model for a better accuracy. On the other hand, some studies shows less favorable opinions regarding the models' accuracy. Cecchini, Aytug, Koehler, & Pathak (2010) applied the Beneish M score model and concluded that it can correctly classify the analyzed data in 40.16% of the cases.

Nonetheless, the research studies show in general, that the Beneish M-score model can improve the auditors' capabilities to detect accounting fraud, as it aids effectively in its detection and should be included as an analytic audit technique.

The Beneish model is used in this instance as a data mining technique, for exploring and analysis of large amounts of data, in order to discover new and significant models and rules. In our research, we applied the Beneish model and afterwards, we developed a tax evasion analysis model by use of the discriminant analysis in IBM SPSS Statistics software, by applying the information in Wagner (2015) and Field (2013). Such analysis is useful for classifying firms in evaders and non-evaders for the specific geographical area studied, that could be optimized and enhanced in order to be applied nationwide.

Due to Romania's social and economic particularities, the model, that in the present day can be considered a validated one through the above mentioned research studies, is still relevant. The transition to a free economic market in Romania was made slowly and because of this, the specific legislation was elaborated with a considerable delay, which implies that the fraudulent mechanisms used in Romania are still classic.

The research advances for testing the following working hypotheses:

Hypothesis 1: *Tax evasion risk can be detected using Beneish model.*
Hypothesis 2: *There is a strong connection between accounting fraud risk and fiscal risk.*
Hypothesis 3: *A model can be developed for classifying firms in tax evaders and non-evaders based on professor Beneish indices.*

Even if fraud, as a generic term includes tax evasion also, the fraud committed for instance in order to improve the performance of the entity by artificially increasing the turnover does not imply tax evasion risk manifestation at the level of the studied entity, the objective of such manipulations being mainly that of deceiving the potential investors in order to attract the necessary financing and not in order to circumvent the compliance with tax obligations. However, theoretically, a manifestation in a certain period of this kind of behavior, can lead in the next period to the desire to cancel the fiscal effect of the behavior.

Moreover, the detected fraud risk at the level of an entity is in a tight connection with tax evasion risk that manifests at the level of its business partners that are situated along the transactional chain. Thus, if the fictitious revenues registered by the studied entity are invoiced to different economic entities, there have to be taken into account the fiscal consequences of registering fictitious expenses by these entities, and the fiscal undue advantages generated at the level of the final beneficiary situated at the end of the transactional chain, in this case the studied entity being an accomplice to tax evasion crimes.

If conclusive results are obtained from this research, this model could be developed and adapted to the national specificity, and could be used by the tax authorities as a component of the risk assessment analysis – risk that could manifest itself in different forms: non-compliance risk, tax evasion risk, insolvency risk, regarding the taxpayer behavior, and by the auditors and even by entities from the private sector in the due diligence phase, when selecting potential business partners.

In order to verify the stated hypotheses a sample of economic entities will be selected using open sources, that is the courts portal (Romanian Justice Department, n.d.), from the North-Eastern region of Romania (the counties Suceava, Botoşani, Iaşi, Vaslui, Bacău and Neamţ) that have been sent to court for tax evasion crimes. The data will be extracted from the cases that have been sent to the tribunals as trial courts of first instance, that in penal matters have the legal competence for judging tax evasion crimes.

As a limitation of the research, the identified sample will not be composed exclusively of legal persons that have been found guilty of tax evasion crimes, but only sent to court for alleged tax evasion crimes. This method of selection was agreed upon taking into account the fact that the available published data from the courts portal is not uniformly presented in what concerns the parties from the case, in some cases as indicted party being mentioned only the natural person who is to be held criminally responsible, the legal persons involved being only sometimes mentioned as a civilly liable party, from this point of view being difficult to identify the state and result of legal procedures regarding a certain legal economic entity.

As a selection methodology of the data, the following algorithm was applied:

Step 1 – accessing the trial courts portal – selecting the court – interrogating the database by the keyword "evasion" – ordering the files starting from the most fresh one – identifying the economic entities that have been indicted or that appear as a civilly liable party.

After this step 30 economic entities were selected.

Step 2 – extracting from the central database of the Ministry of Public Finance, the fiscal information and financial statements section (Romanian Ministry of Finance, n.d.) the main indicators from the financial statements of the selected entities and extracting the necessary parameters in order to compute the indices proposed by Beneish for the 5-variable model, that is:

- Days Sales in Receivables Index (DSRI);
- Gross Margin Index (GMI);
- Asset Quality Index (AQI);
- Sales Growth Index (SGI);
- Sales General and Administrative Expenses Index (SGAI).

The necessary parameters are: net sales, receivables, current assets, non-current assets, total assets, total expenses, net profit/loss, gross profit/loss and total debt and they were extracted for three consecutive years, depending on the availability of the data these years being in the interval 2011 – 2016. If the value of the financial indicators from the balance sheet and profit and loss account was zero, the conventional value "1" was used in order to be able to compute the necessary indices. The data for the population from the sample was extracted for those intervals in order to be able to compute the M-score for two periods (the indicators of the baseline financial period are to be computed relative to the previous financial period).

All these parameters were extracted as initially it was intended for the 8-variable Beneish model to be used, but it was concluded that the available indicators on the official site of the Ministry of Public Finance do not allow for all the variables to be computed, so we applied the 5-variable model.

Step 3 – computing by use of Microsoft Excel the variables on the basis of the selected parameters representing the values of the indicators from the financial statements of the selected entities.

The formulas used when computing the variables for the financial period 2015, relative to the previous financial period (2014) are the following:

- Days Sales in Receivables Index (DSRI):

$$DSRI = (\frac{R2015}{TS2015})/(\frac{R2014}{TS2014}) \tag{1}$$

- Gross Margin Index (GMI) – Computed by dividing the gross profit margin from the current period to the value from the previous period, according to available data:

$$GMI = (\frac{GP2015}{TS2015})/(\frac{GP2014}{TS2014}) \tag{2}$$

- Sales Growth Index (SGI):

$$SGI = (\frac{TS2015}{TS2014}) \tag{3}$$

- Sales General and Administrative Expenses Index (SGAI):

$$SGAI = (\frac{TE2015}{TS2015})/(\frac{TE2014}{TS2014}) \tag{4}$$

Where,

R2015 = receivables reported at the end of the year 2015;
R2014 = receivables reported at the end of the year 2014;
TS2015 = total sales (net turnover) reported at the end of the year 2015;
TS2014 = total sales (net turnover) reported at the end of the year 2014;
TE2015 = total expenses reported at the end of the year 2015;
TE2014 = total expenses reported at the end of the year 2014;
GP2015 = gross profit/loss reported at the end of the year 2015;
GP2014 = gross profit/loss reported at the end of the year 2014.

As a limitation of the research, we have to mention the fact that, in this phase an index was not computed, that is the Asset Quality Index (AQI), due to the unavailability of the data relative to structure ratios of assets. Instead of this index the test values proposed by Beneish were used, in order to not influence the structure of the model, the data used being that from the table of the median value of Beneish (1999) variables.

Step 4 – using the computed variables the M-score was calculated according to Beneish equation, as follows:

$$M = -6.065 + (.823 * DSRI) + (.906 * GMI) + (.593 * AQI) + (.717 * SGI) + (.172 * SGAI) \tag{5}$$

Empirically, the economic entities that have higher M-scores are more inclined to perpetrating fraud. However, the M-score is a probabilistic model that does not have 100% accuracy in detecting fraud. M-score can be converted to probabilities using the NORMSDIST function from Microsoft Excel, according to the data presented below:

Table 1: The results of applying the Beneish model on the economic entities that present tax evasion risk

Entities	DSRI	GMI	AQI*	SGI	SGAI	M-SCORE	Probab-ility	Groups (M-score > -2.22)
E1 2014	0.62	0.45	1.00	1.89	0.75	-3.07	0.11%	FALSE
E1 2015	1.62	0.48	1.00	1.41	0.85	-2.54	0.55%	FALSE
E2 2014	19.10	7.91	1.00	0.03	5.20	18.33	100.00%	TRUE
E2 2015	2.50	0.54	1.00	1.05	0.54	-2.07	1.90%	TRUE
E3 2012	0.48	4.92	1.00	0.80	1.21	0.16	56.44%	TRUE
E3 2013	0.89	-0.11	1.00	1.25	0.75	-3.81	0.01%	FALSE
E4 2015	0.66	0.30	1.00	1.14	1.06	-3.66	0.01%	FALSE
E4 2016	0.56	-0.13	1.00	0.74	1.05	-4.42	0.00%	FALSE
E5 2014	0.75	0.50	1.00	1.50	0.74	-3.20	0.07%	FALSE
E5 2015	0.75	1.35	1.00	1.39	0.93	-2.47	0.68%	FALSE
E6 2014	1.07	1.97	1.00	1.45	0.96	-1.60	5.45%	TRUE
E6 2015	2.65	1.79	1.00	0.68	0.94	-1.02	15.47%	TRUE
E7 2014	64,829.03	0.79	1.00	0.15	0.96	53,349.81	100.00%	TRUE
E7 2015	37,258.00	-5.73	1.00	0.00	0.85	30,652.82	100.00%	TRUE
E8 2014	4.11	-0.01	1.00	1.15	0.95	-1.11	13.39%	TRUE
E8 2015	0.12	-94.66	1.00	0.21	1.73	-90.69	0.00%	FALSE
E9 2014	1.07	0.25	1.00	0.59	1.15	-3.75	0.01%	FALSE
E9 2015	4.20	6.05	1.00	0.08	0.79	3.66	99.99%	TRUE
E10 2014	0.59	0.17	1.00	1.70	1.10	-3.42	0.03%	FALSE
E10 2015	1.67	1.83	1.00	0.72	0.98	-1.76	3.90%	TRUE
E11 2014	1.10	10.63	1.00	1.41	0.87	6.22	100.00%	TRUE
E11 2015	0.19	0.14	1.00	3.84	1.14	-2.24	1.24%	FALSE
E12 2013	0.22	1.85	1.00	13.75	1.49	6.50	100.00%	TRUE
E12 2014	5.26	0.77	1.00	1.47	0.83	0.75	77.29%	TRUE
E13 2013	13.42	-0.01	1.00	0.07	0.43	5.69	100.00%	TRUE
E13 2014	30.51	67.59	1.00	0.03	0.29	80.95	100.00%	TRUE
E14 2014	195.41	32.73	1.00	0.00	8.55	186.48	100.00%	TRUE
E14 2015	0.86	0.93	1.00	1.17	0.60	-2.98	0.14%	FALSE
E15 2014	0.72	1.17	1.00	0.92	1.06	-2.97	0.15%	FALSE
E15 2015	3.95	1.18	1.00	0.24	1.08	-0.80	21.32%	TRUE
E16 2014	1.08	-2.50	1.00	1.09	1.03	-5.89	0.00%	FALSE
E16 2015	1.23	-0.10	1.00	1.29	0.96	-3.45	0.03%	FALSE
E17 2014	61,850.46	-1,283.43	1.00	0.00	-560.63	49,638.24	100.00%	TRUE
E17 2015	1.00	-2.36	1.00	1.00	-2.36	-6.48	0.00%	FALSE
E18 2014	56,800.00	1,870.40	1.00	0.00	1,570.79	48,705.69	100.00%	TRUE
E18 2015	0.00	0.00	1.00	1.00	0.00	-4.76	0.00%	FALSE
E19 2014	1.31	-11.18	1.00	0.47	1.07	-14.00	0.00%	FALSE
E19 2015	27.45	49.74	1.00	0.03	4.33	62.95	100.00%	TRUE
E20 2014	7,370.99	21,819.54	1.00	0.00	53,508.18	35,032.76	100.00%	TRUE
E20 2015	1.00	0.03	1.00	1.00	0.01	-3.91	0.00%	FALSE
E21 2014	0.78	0.87	1.00	0.75	1.00	-3.33	0.04%	FALSE
E21 2015	0.54	0.26	1.00	11.85	1.02	3.87	99.99%	TRUE
E22 2014	1.08	2.03	1.00	1.40	0.84	-1.59	5.63%	TRUE
E22 2015	1.16	1.23	1.00	0.95	1.00	-2.55	0.54%	FALSE
E23 2012	2.20	0.96	1.00	0.75	0.99	-2.08	1.88%	TRUE
E23 2013	1.63	-50.22	1.00	0.87	1.12	-48.82	0.00%	FALSE
E24 2014	0.98	-0.23	1.00	1.66	1.04	-3.50	0.02%	FALSE
E24 2015	1.06	-1.94	1.00	0.57	0.98	-5.78	0.00%	FALSE
E25 2013	1.51	234.04	1.00	0.75	-0.31	208.29	100.00%	TRUE
E25 2014	1.31	0.76	1.00	1.53	-0.02	-2.61	0.46%	FALSE
E26 2014	0.27	0.15	1.00	1.84	0.43	-3.72	0.01%	FALSE
E26 2015	3.74	1.10	1.00	0.74	1.01	-0.69	24.50%	TRUE

E27 2014	1.27	0.76	1.00	1.04	0.93	-2.83	0.23%	FALSE
E27 2015	1.33	1.44	1.00	0.73	1.11	-2.35	0.93%	FALSE
E28 2014	3.57	1.61	1.00	0.55	0.98	-0.51	30.56%	TRUE
E28 2015	2.96	2.02	1.00	0.46	0.68	-0.76	22.26%	TRUE
E29 2014	2.51	-12.01	1.00	0.40	1.19	-13.80	0.00%	FALSE
E29 2015	0.80	1.13	1.00	1.34	0.96	-2.67	0.38%	FALSE
E30 2014	1.24	22.99	1.00	0.96	1.47	17.32	100.00%	TRUE
E30 2014	0.66	3.84	1.00	1.54	0.65	-0.23	40.76%	TRUE

Note: * Constant at the test value proposed by Beneish
Source: Authors' own computations

It can be observed that the economic entities E7, E17, E18 and E20 register very high values for the M-score. This is due to the fact that the financial statements submitted to tax authorities and available on the Romanian Ministry of Finance' website contain anomalies (the economic entity E7 does not report any receivables in 2013 and in 2015 it does not report any turnover; E17, E18 and E20 do not report a turnover in 2014).

5. RESULTS AND DISCUSSION

From the evaluated sample, containing 60 observations (30 entities x 2 financial years), in 30 cases from 60 (50%), the M-score indicator had a lower value than the reference value, indicating the possibility of the existence of fraud. On the other hand, from a total of 30 entities studied, 23 of them (76,67%), registered a higher M-score than the reference value of -2.22, thus showing indications of financial fraud (Mantone, 2013; Tarjoa, & Herawati, 2015), in one of the monitored periods, manifesting a shifting behavior within the studied period, at least in one year using fraudulent practices.

In Table 2 below, a short presentation of the possible interpretation of the evolution of the computed indices according to Beneish model was made:

Table 2: Possible Interpretation of The Evolution of The Computed Indices According to Beneish Model

DSRI – Days Sales in Receivables Index	- a disproportionate increase of receivables relative to sales can contain indications of revenue manipulation – the artificial growth of the turnover in order to attract investors, will lead to a high value of the unrecovered receivables, the desire to present a favorable view on the financial position of the entity by supra valuating assets, artificial increase of receivables, etc.
GMI – Gross Margin Index	- a significant increase in time of gross profit ratios can be explained by alleged fraud regarding revenue recognition, in order to present a modified (increased) performance of the entity; - deterioration of gross profit indicator is a negative signal on the entity's perspectives that can determine it to use creative or fraudulent accounting techniques.
SGI – Sales Growth Index	- the significant variation can contain indications of the existence of irregularities in revenue recognition; - an entity that registers an increasing turnover is considered to be more tempted by fraud because its financial position and financing

	needs are putting pressure on the managers in order for them to reach the set objectives.
SGAI – Sales General and Administrative Expenses Index	- reduced values of the index can be translated by the desire to manipulate/modify the result, by not including or not recognizing entirely expenses in the course of the financial period, with the purpose of attracting potential investors; - high values of the index can be interpreted by the desire to manipulate/modify the result, by registering fictitious expenses.

Source: Authors' own projections

Step 5 – on the basis of the computed variables, excluding the outliers (the indices computed for E7 for 2014 and 2015 and those computed for E17, E18 and E20 for 2014) by use of statistical software SPSS 19.0 the discriminant analysis was performed, in order to identify the variables that have significant impact on group discrimination and afterwards in order to generate a model for detecting tax evasion – which delivered the following descriptive statistics according to the output data:

Table 3: Descriptive Statistics of The Studied Groups

Groups	Variables	Mean	Std. deviation
1 – that contain fraud indications	DSRI	13.223224	38.829783
	GMI	18.333336	47.998756
	SGI	1.679303	3.3961007
	SGAI	1.472028	1.8694416
2 – that do not contain fraud indications	DSRI	0.9375	0.5026
	GMI	-5.4446	19.3791
	SGI	1.1764	0.6585
	SGAI	0.778	0.7008
Total	DSRI	6.521919	26.615101
	GMI	5.36354	36.99199
	SGI	1.404975	2.3286854
	SGAI	1.093453	1.3923588

Source: Authors' own projections using SPSS

According to the equality of group means test, there was concluded that the variable GMI has Sig. = .016 < 0.05, meaning there are significant differences between the variable's mean values between the two groups. The lowest influence on group discrimination can be attributed to SGI variable (Sig. = .430):

Table 4: Results of Tests of Equality of Group Means

Tests of Equality of Group Means					
Variable	**Wilks' Lambda**	**F**	**df1**	**df2**	**Sig.**
DSRI	.946	3.014	1	53	.088
GMI	.896	6.174	1	53	.016
SGI	.988	.632	1	53	.430
SGAI	.937	3.548	1	53	.065

Source: Authors' own projections using SPSS

The Wilks ‘Lambda test revealed that the centroids of the groups do not significantly differ (Sig. = .032< 0.1), thus showing the model used for separating them is not very sustainable only on these variables.

Table 5: Results of Wilks' Lambda test

Wilks’ Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.813	10.534	4	.032

Source: Authors’ own projections using SPSS

The impact of the variables on the model is captured in the table below, the magnitude of the influence being reflected by the value in module and the sense by the sign in front of the figures:

Table 6: Discriminant function coefficients

Standardized Canonical Discriminant Function Coefficients	
Variables	**Function**
DSRI	-0.043
GMI	0.807
SGI	0.354
SGAI	0.678

Source: Authors’ own projections using SPSS

In what concerns the result of the testing of the hypotheses, we conclude the following:

Hypothesis 1*: Tax evasion risk can be detected using Beneish model.*

Applying the model lead to classifying approximately 77% of the entities committing tax evasion in the group containing entities that use manipulations of accounting information and that report fraudulent financial statements, however in what concerns the studied observations, only in 50% of the cases it has been detected that the financial statements of the entities contain fraudulent elements.

Thus, there have to be included observations regarding the period in which the tax evasion behavior manifested in order to obtain pertinent results, and also, there has to be considered the specificity of the simulated behavior of the tax evading entities that, in order not to raise any suspicions, are submitting fiscal declarations and annual financial statements and half-yearly accounting reports that apparently contain data and information complying with legal norms and regulations, that do not raise red flags at an incipient analysis of such data. Nevertheless, subsequently these entities *evaporate* without paying to the state budget the fiscal taxes and duties that have been established, registered and declared.

Moreover, in order to obtain a pertinent result on the research, the sample has to be extended at national level, not only for the North-Eastern region and it has to be taken into account the possibility of using other data as well, such as fiscal data and other financial ratios that could be determined dependent upon the availability of the data. In the current state the result is not conclusive.

Hypothesis 2*: There is a strong connection between accounting fraud risk and fiscal risk.*

According to the above mentioned information, in 50% of the cases it has been detected that the financial statements of the studied entities contain fraudulent elements. According to , From this point of view, the research result is not conclusive. In order to obtain conclusive results a new selection of the variables has to be performed, the sample has to be extended and eventually the sample data has to be structured depending on: the size of the entities, field of activity, etc.

Hypothesis 3*: A model can be developed for classifying firms in tax evaders and non-evaders based on professor Beneish indices.*

After performing the discriminant analysis in SPSS of Beneish's indices computed on the selected sample of economic entities a discriminant function was generated, that could be useful for classifying firms in tax-evaders and non-evaders, although such model could be optimized and enhanced by adding other variables also. The function is as follows:

$$Group\ classification = -.043\ x\ DSRI + .807\ x\ GMI + 354\ x\ SGI + .678\ x\ SGAI \qquad (6)$$

Beneish model could also be used as a data mining technique, which has been defined as a process of exploration and analysis, by use of automated or semi-automated methods, of large volumes of data, and also of discovery of new and significant models and rules (Berry & Linoff, 1997).

Thus, starting from Beneish indices, in order to test the confidence in the data presented above, a discriminant analysis will be conducted by use of statistical software SPSS for two groups. Group 1 contains tax evading entities classified as having the highest probability of committing financial statement fraud (the sample was selected from the existent data – 20 observations) and group 2 contains economic entities from the same region and field of activity considered honest (a new sample that supposed following the steps from the above described algorithm in order to select the necessary data). The final objective of such modeling is obtaining information regarding the influence of the variables on the discriminant function that determines the classification of the entities in one of the groups, in order to validate the previous conclusions, taking into account the fact that Beneish model was applied on tax evading entities, of which no information was known regarding the quality of the accounting information from the financial statements (if it contains fraud indications or not).

After performing the analysis, the following output data was obtained:

Table 7: Descriptive Statistics on The Discriminant Analysis (Confidence Test)

Groups	Variables	Mean	Std. deviation
1 – that contain fraud indications	DSRI	20.31011	49.49129
	GMI	29.66175	60.04534
	SGI	2.221712	4.345637
	SGAI	1.854187	2.362616
2 – that do not contain fraud indications	DSRI	-31.0223	142.4279

	GMI	0.662523	3.315425
	SGI	1.26258	0.500489
	SGAI	1.004621	0.18064
Total	DSRI	-9.0227	114.057
	GMI	13.09076	41.26429
	SGI	1.673637	2.854451
	SGAI	1.368721	1.58071

Source: Authors' own projections using SPSS

According to the equality of group means test, it has been concluded that also the variable GMI has Sig. = .038 < 0.05, meaning there are significant differences of the variable's mean values between the two groups. The lowest influence on group discrimination can be attributed to SGI variable (Sig. = .333):

Table 8: Results of Tests of Equality of Group Means (Confidence Test)

Tests of Equality of Group Means					
Variable	**Wilks' Lambda**	**F**	**df1**	**df2**	**Sig.**
DSRI	.949	1.776	1	33	.192
GMI	.875	4.693	1	33	.038
SGI	.972	.967	1	33	.333
SGAI	.927	2.592	1	33	.117

Source: Authors' own projections using SPSS

The Wilks 'Lambda test revealed that the centroids of the groups do not significantly differ (Sig. = .036< 0.1), thus showing the model used for separating them, is not very sustainable only on these variables.

Table 9: Results of Wilks' Lambda test (confidence test)

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.718	10.249	4	.036

Source: Authors' own projections using SPSS

In this case, the discriminant function can be written as follows:

$$Group\ classification\ = .298\ x\ DSRI\ +\ .804\ \ x\ GMI\ +\ .541\ x\ SGI\ +\ \ .575\ x\ SGAI \qquad (7)$$

Table 10: Discriminant function coefficients (confidence test)

Standardized Canonical Discriminant *Function* Coefficients	
Variables	**Function**
DSRI	0.298
GMI	0.804
SGI	0.541
SGAI	0.575

Source: Authors' own projections using SPSS

Thus, after retesting the model in order to validate the confidence in the obtained results, the hierarchical order of the variables' impact on the initial model was confirmed. In this case, the Gross Margin Index (GMI) had the highest influence on group discrimination, thus having the highest impact on the model, while the Sales Growth Index (SGI) had the lowest.

6. CONCLUSION

Considering that there is a dependency of taxation on the accounting informational system, through logical construction it can be argued that an instrument useful for detecting financial and accounting fraud such as the Beneish model, can also be effective for detecting fiscal fraud – that is the indications for the manifestation of the tax evasion risk.

Applying the model lead to including approximately 77% of the entities committing tax evasion in the group containing entities that use manipulations of accounting information, however in what concerns the studied observations, only in 50% of the cases it has been detected that the financial statements of the entities contain fraudulent elements.

After performing the discriminant analysis in SPSS of Beneish's indices computed on the selected sample of economic entities, a discriminant function was generated, that could be useful for classifying firms in tax-evaders and non-evaders, although such model should be optimized and enhanced by adding other variables also. It was concluded that the variable Gross Margin Index (GMI) had the highest influence on the model, followed by the variable Sales General and Administrative Expenses Index (SGAI). Therefore, the model developed by professor Beneish could be used as an early indication in the incipient phase of a research on developing a model that can detect tax evasion.

As future research perspectives, in order to create a sustainable model for detecting tax evasion, there have to be included variables built on fiscal data (depending on the availability of such data) and the sample of tax evading entities that will be studied has to be extended, in order to ensure data representativeness and conclusiveness.

At the same time, another sample of entities allegedly honest will be selected having the same size, activating in the same geographical area, in order to be able through an intelligent predictive model, combined with a logistical regression model and some algorithm for evolution computation or harmonization simulation (as a support for the selection of the variables analysis) to obtain a sustainable discriminant function that can classify the entities in risk groups in what concerns tax evasion risk. The possibility of structuring the data depending on the size of the entities, the field of activity, and the geographical location in order to address certain latitudinal and longitudinal specificities has to be taken into account also.

Moreover, by direct observation on the main indicators from the financial statements of the studied entities when testing the confidence in the data obtained, it was observed the fact that an inclusion of non-financial variables as model parameters would be appropriate, from the informative data to the financial statements, such as the average number of employees – that presented significant variations relative to the identified groups within the studied period.

Also, observations regarding the period in which the tax evasion behavior manifested have to be included in the model, in order to be able to obtain pertinent results. In the current state of the research the result is not a conclusive one, the tested hypothesis being partially validated. A mechanism for detecting fraud and tax evasion could be useful for state authorities, even the one from the secluded case in Romania, because although it is based on a geographical cluster, it could be optimized and developed further in order to be applied at national level or to fit the national specificity of each country, thus having a very large applicability. Such mechanism cannot ensure that fraud is not happening, but by detecting the most vulnerable economic areas, the policymakers could keep a controlled dimension of the phenomena by prompt decisions regarding the prevention and control of fraud and tax evasion in those areas.

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REFERENCES

Artavanis N., Morse A., & Tsoutsoura M. (2015). *Measuring Income Tax Evasion using Bank Credit: Evidence from Greece*. Chicago Booth Research Paper No. 12-25. Fama-Miller Working Paper.

Beneish, M. D. (1999). The Detection of Earnings Manipulation. *Financial Analysts Journal, 55*(5), 24–36. doi: https://doi.org/10.2469/faj.v55.n5.2296

Berry, M., & Linoff, G. (1997). *Data Mining Techniques for Marketing Sales and Customer Support*. New Jersey: Wiley.

Bunget, O. C., & Dumitrescu A. C. (2008). Accounting Treatment of Deferred Income Taxes According to The Requirements of The Romanian Accounting Regulations. *The Annals of University of Oradea – Economic Science, XVII*(3), 1039-1043. Retrieved from http://steconomiceuoradea.ro/anale/volume/2008/v3-finances-banks-accountancy/190.pdf

Cecchini, M., Aytug, H., Koehler, G. J., & Pathak, P. (2010). Making words work: Using financial text as a predictor of financial events. *Decision Support Systems, 50*(1), 164–175. doi: https://doi.org/10.1016/j.dss.2010.07.012

Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (2011). Predicting Material Accounting Misstatements. *Contemporary Accounting Research, 28(*1), 17–82. doi: 10.1111/j.1911-3846.2010.01041.x

Dikmen, B., & Kucukkocaoglu, G. (2009). The Detection of Earnings Manipulation: The Three-Phase Cutting Plane Algorithm Using Mathematical Programming. *Journal of Forecasting, 29*(5), 442-466. doi: 10.1002/for.1138

Directorate General Taxation and Customs Union (2017). *Study and Reports on the VAT Gap in the EU-28 Member States: 2017 Final Report.* Retrieved from https://ec.europa.eu/taxation_customs/sites/taxation/files/study_and_reports_on_the_vat_gap_2017.pdf

Erdoğan, M., & Erdoğan, E. O. (2020). Financial Statement Manipulation: A Beneish Model Application. In S. Grima, E. Boztepe, & P. J. Baldacchino (Eds.), *Contemporary Issues* *in Audit Management and Forensic Accounting* (pp. 173–188). Bingley: Emerald Publishing Limited.

Fekete, S., Cuzdriorean D. D., Sucală L., & Matiş D. (2009). An attempt at measuring the Fiscal Influence Over Accounting of Romanian Listed Companies. *SSRN e-Library*.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics* (4^{th} Eds.). Sage Publication Ltd.

Fischthal, S. (1998). *Neural network/conceptual clustering fraud detection architecture* (US Patent 5822741). U.S. Patent and Trademark Office. https://patentimages.storage.googleapis.com/2b/14/3e/eeefb00edc9489/US5822741.pdf

Gupta, M., & Nagadevara, V., (2007). Audit Selection Strategy for Improving Tax Compliance: Application of Data Mining Techniques. In A. Agarwal, & V. Ramana (Ed.) *Foundations of E-Government, Proceedings of the eleventh International Conference on e-Governance* (pp. 28-30). Hyderabad, India.

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), 146-163.

Hashimzade, N., Myles, G., Page, F., & Rablen, M. (2015). The use of agent-based modelling to investigate tax compliance. *Economics of Governance*, *16*(2), 143–164. doi: 10.1007/s10101-014-0151-8

Lee, M., & Colbert, J. L. (1997). Analytical procedures: management tools for monitoring controls. *Management Decision*, *35*(9), 682-688.

Lenard, M. J., & Alam, P. (2010). An Historical Perspective on Fraud Detection: From Bankruptcy Models to Most Effective Indicators of Fraud in Recent Incident. *Journal of Forensic and Investigative Accounting, 1*(1), 1-27.

Liou, F. M. (2008). Fraudulent financial reporting detection and business failure prediction models: a comparison. *Managerial Auditing Journal*, *23*(7), 650-662.

MacCarthy, J. (2017). Altman Z-score, Beneish M-score, Corporate Failure, Financial Statements, Fraud. *International Journal of Finance and Accounting, 6*(6), 159–166.

Mahama, M. (2015). Detecting Corporate Fraud and Financial Distress Using the Altman and Beneish Models. *International Journal of Economics, Commerce and Management, 3*(1), 1-18.

Mantone, P. S. (2013). *Using Analytics to Detect Possible Fraud: Tools and Techniques*. New Jersey: Johm Wiley & Sons, Inc.

Mehta, A., & Bhavani, G. (2017). Application of Forensic Tools to Detect Fraud: The Case of Toshiba. *Journal of Forensic and Investigative Accounting, 9*(1), 692-710.

Mekic, A., Halilbegovic, S., & Huric, A. (2017). Forensic Accounting As A Solution To Manipulative Accounting Of Sme's In Bosnia And Herzegovina. *Ecoforum*, *6*(2), 1-8.

Nyakarimi, S. N., Kariuki, S. N., & Kariuki, P. W. (2020). Financial Statements Manipulations Using Beneish Model and Probit Regression Model. A Case of Banking Sector in Kenya. *European Online Journal of Natural and Social Sciences*, *9*(1), 253-264.

Omar, N., Koya, R. K., Sanusi, Z. M., & Shafie, N. A. (2014). Financial Statement Fraud: A Case Examination Using Beneish Model and Ratio Analysis. *International Journal of Trade, Economics and Finance, 5*(2), 184–186. doi: 10.7763/IJTEF.2014.V5.367

Paliu-Popa L., & Ecobici N. (2007). *Accounting Implications of Taxation* 2007. MPRA Paper No. 12186.

Ristea, M. (2003), *Bază şi alternativ în contabilitatea întreprinderii*. Bucharest: Economic Forum.

Romanian Justice Department (n.d.). *Romanian Courts Portal*. Retrieved from http://portal.just.ro/SitePages/acasa.aspx

Romanian Ministry of Finance (n.d.). *Fiscal Information and Financial Statements*. Retrieved June 21, 2017, from http://www.mfinante.gov.ro/rol.html?pagina=acasa

Romanian National Fiscal Council (2013). *Annual Report 2013*. Retrieved from http://www.consiliulfiscal.ro/

Schneider, F., Buehn A., & Montenegro, C. (2010). *Shadow economies all over the World—New estimates for 162 Countries from 1999 to 2007*. World Bank Policy Research Working Paper WPS5356.

Spathis, C., Doumpos, M., & Zopounidis, C. (2002). Detecting falsified financial statements: a comparative study using multicriteria analysis and multivariate statistical techniques. *European Accounting Review, 11*(3), 509-535.

Tarjoa, & Herawati, N. (2015). Application of Beneish M-Score Models and Data Mining to Detect Financial Fraud. *Procedia - Social and Behavioral Sciences, 211*, 924 – 930.

Vladu, A. B., Amat, O., & Cuzdriorean, D. D. (2017). Truthfulness in Accounting: How to Discriminate Accounting Manipulators from Non-manipulators. *Journal of Business Ethics, 140*(4), 633–648. doi: 10.1007/s10551-016-3048-3

Volkov, M. (2020). Beneish Model as a Tool for Reporting Quality Estimation: Empirical Evidence. In T. Antipova (Ed.), *Integrated Science in Digital Age 2020* (pp. 60–68). NY: Springer International Publishing.

Wagner, W. E. (2015). *Using IBM SPSS Statistics For Research Methods And Social Science Statistics*. California: SAGE Publication.

Wu, R.-S., Ou, C.-S., Lin, H.-Y., Chang, S.-I., & Yen, D.C. (2012). Using data mining technique to enhance tax evasion detection performance. *Expert System with Application, 39*, 8769–8777.