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Use of Regression Models when Performing Fraud Risk Assessment Procedures in the Audit Process

Andrey Vladimirovich Bakhteev[1], Sergey Valentinovich Arzhenovskiy[2], Natalya Nikolayevna Khakhonova[3], Yelena Vyacheslavovna Kuznetsova[4]

Abstract:

The article provides an overview of current research in the use of regression models when performing assessment procedures of material misstatement risks due to fraud in the financial statement audit. The authors were reviewing regression models predicting deliberate distortion of financial statements, developed by M. Beneish and J. Jones. In addition, they consider the later modifications to these models, applicable in the course of the audit process to estimate the material misstatement risk on the basis of meso-economic, operational, scaling, and other factors affecting the operations of reporting accountants.

The specific features, advantages, disadvantages and the use of different types of regression models in the audit process are described. The criteria for comparison are formulated, and the comparative analysis of adapting the best-known features of regression models to the challenges of fraud risk assessment for financial statements in the audit process is carried out. The conclusions about the possibilities of use and a range of different types of regression models when initiating the fraud risk assessment procedures to the financial statements in the audit process are formulated. The limitations, inherent of such models are explained.

Keywords: *Risk of material misstatement, financial statement fraud, earnings management, risk assessment procedure, logit model, nonfinancial measures.*

JEL Classification: *C20, M42*

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[1]Corresponding author, Ph.D. (Economics), Associate Professor, Accounting and Economics Department, Rostov State University of Economics, Rostov-on-Don, Russian Federation, +7 863 261 38 92, a_bakhteev@mail.ru
[2]Ph.D. (Economics), Professor, Accounting and Economics Department, Rostov State University of Economics, Rostov-on-Don, Russian Federation
[3]Ph.D. (Economics), Professor, Accounting and Economics Department, Rostov State University of Economics, Rostov-on-Don, Russian Federation
[4]Ph.D. (Economics), Professor, Accounting and Economics Department, Rostov State University of Economics, Rostov-on-Don, Russian Federation

1. Introduction

The results of the constantly ongoing research in the field of corporate fraud (PwC, 2016) indicate that one of the most significant threats to the modern investment community still is deliberate falsification of public financial statements of companies. Therefore, one of the areas of the constant improvement process in the professional environment is a search of methods to adequately identify the risks of material misstatement resulting from financial statements fraud (Further on RMMF).

Drawing attention of researchers in this field to methodology of risk assessment in the audit process has several reasons: a) in the basis of professional activities of the contemporary auditor there lies a risk-based approach[1], having the COSOERM framework as its conceptual base; b) none of the existing systems of audit standardization, including ISA contains recommendations for practical application of framework provisions of certain standards, that oblige the auditor to identify and assess the risk of material misstatement in financial statements in general and RMMF in particular, while working on the assignment; c) any standardization system of risk management process (eg. ISO/IEC), offers a list of methods that can potentially be used in the risk assessment in any area of economic activity. These risk assessment standards do not aim at adapting any methods to special features of risk assessment within a particular subject area. The selection of specific methods of identification and assessment of RMMF and creation of practical methods on their base is the prerogative of each separate audit company.

The article is an overview of trends and research results in the field of methodological support of RMMF assessment procedures during the audit, which have their results published within the last two decades. The authors review the most relevant regression analysis models, recommended for use as techniques of RMMF assessment, analyze their strengths and weaknesses, areas of possible use in the process of the financial statements audit.

2. Methodology

The process of improving the methodology of audit is accompanied by the increasing amount of research into the development of methodical maintenance of audit RMMF assessment procedures. Among the proposed models and methods of risk assessment the quantitative ones traditionally dominate. Within this framework, the basis for quantitative assessment of RMMF consists of methods given in the group "Risk Management" of ISO/IEC standards. Risk assessment methods standard

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[1]*It should be noted that the last modification of the existing model, proposed by the Committee of Sponsoring Organizations of the Treadway Commission, also known as COSO, is positioned as a model for identifying and assessing the risk of fraud by its developers (authors' note).*

(GOST 2012) contains description and guidelines for the use of more than three dozen methods and risk assessment models. As we noted above, for RMMF assessment you cannot efficiently use all the methods described in the standard. Therefore, only some quantitative methods are applicable in the implementation of RMMF assessment procedures on the financial statements level as a whole, as well as on the level of statement preparation, operation groups and balance (Vasilenko, 2015; Thalassinos and Liapis 2014; Vovchenko *et al.*, 2017; Tcvetkov *et al.*, 2015; Theriou, 2015). During the study, we have formulated the following criteria, complying with which enables us to determine the validity of a particular method / model for RMMF assessment in the audit process: a) availability of source data to calculate the values of the model; b) availability of a uniform scale of normative values, which allows to evaluate the quality of results; c) the precise orientation of the model on the signs of source data manipulation used in calculation; d) the performance efficiency criterion (i.e., costs vs results) when using a method / model for assessing RMMF.

The authors conducted a review of current research in the field of development of methodical support for risk assessment procedures and revealed that methods based on regression analysis models are the most widespread type of RMMF assessment methods in the audit (Sharma and Panigrahi, 2012; Hogan, 2008; Thalassinos and Politis, 2012; Suryanto, 2016; Boldeanu and Tache, 2016).

The *M-score* approach designed by Beneish (1997; 1999) is the best-known of them. The authors specified a regression model of discrete choice which, in their opinion, makes it possible to identify with reasonable certainty the financial statements containing figures subjected to deliberate distortion. The model includes eight explanatory variables: the days sales ratio index (DSRI); the gross margin index (GMI); the asset quality index (AQI); the sales growth index (SGI); the depreciation Index (DEPI); the selling and administrative expenses index (SGAI); the total accruals to total assets index (TATA); the leverage gearing index (LVGI).

The dependent variable M_i is binary and takes the value of 1 for companies that manipulate their financial statements and 0 for the others. The model is as follows:

$$M_i = \mathbf{X}_i\boldsymbol{\beta} + \varepsilon_i,\ i = 1,\ldots, n,$$

where M_i is a dependent binary variable, $\mathbf{X}_i$ is the matrix of explanatory variables, ε_i – random error, i is the index for firms, n is the number of firms. The accounting data, useful for the detection of fraud and assessing the reliability of the accounting profit, is used within the model.

According to Beneish (1999) model estimation obtained with the help of unweighted method of maximum likelihood for panel data on the financial statements of the US companies from 1987 to 1993, is as follows:

$M = -4.840 + 0.920DSRI + 0.528GMI + 0.404AQI + 0.892SGI + 0.115DEPI - 0.172SGAI - 0.327LVGI + 4.679TATA.$

The priori probability of financial statement fraud was 0.028. According to the model, the predicted probability of statement fraud averaged to 0.237. An interesting fact is that the authors did not aim to developing a model of RMMF identification and assessment for the audit. According to Beneish (1999) the model is designed to identify the facts of a company earnings management[1]. The *M-score* model has been widely used in RMMF assessment when auditing financial statements due to the fact that revenue (income) is the key indicator for the target users of financial statements when making investment decisions. The income is the basis of contemporary simulation predictive models of a company's commercial development.

Subsequently, Beneish's model has repeatedly undergone changes. For example, *in* the work by Roxas (2011), when calculating the composite index of the *M-score*, concluded that only five of the seven previously proposed explanatory variables are significant. The probability value, when the risk of fraud in financial statements is considered to grow high, is 0.276.

Within the RMMF assessment model for the audit, developed by Spathis (2002) it was proposed to use Altman's *Z-score* value. The author selected 10 values as indicators of potential fraudulent financial statements. They are the following: the ratio of debt to equity; resource productivity; return on sales; the ratio of receivables to sales; return on assets; the ratio of net working capital to assets; the ratio of gross profit to assets; the ratio of stocks to sales; the ratio of total debt to assets; Altman's *Z-score*.

In the model proposed the dependent variable *FFS* takes the value 1 if a firm had falsified accounts and 0 if there are no deliberate distortions in the audited financial statements. Further, a logit model with the above explanatory variables is used. According to the author's design, the model can be specify both using *Z-score* and without it. Using *Z-score* aims at evaluating the relationship between the critical financial situation of the company and the falsification of its financial statements. In the course of a step-by-step empirical analysis, conducted by Spathis (2002) using the data of Greek listed companies it was found that the ratio of stocks to sales proved to be statistically positively significant in both models. An increase in stocks, coupled with low turnover of stocks in relation to sales, should lead to the increase of the RMMF value by the auditor. Thus, the growth of the *Z-score* indicator shows a decline in the probability of substantial deliberate misstatement of the financial

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[1] Earnings management is the use of methods of company's revenues and expenses recognition, legally established by the accounting standards, to prepare financial statements, representing an excessively positive picture of its economic activity and financial situation (authors' note).

statements. The author was able to adequately classify about 84% of firms constituting the sample on the basis of the model constructed.

At their core, Spathis's model, as well as Roxas's model, is special cases of discrete choice models that demonstrate the capacities and limitations of using such models for external environment of listed companies existing in a single national economy (Greece). The high productivity of Spathis's model proves, firstly, vast possibilities of its application under specific conditions, and, secondly, the need to study the specificity of the regression model of discrete choice, which will work correctly when assessing RMMF with listed (or unlisted) companies in, e.g., the Russian investment environment.

These regression models meet all the criteria set out above, which determines their function as a tool for RMMF assessment. Despite this, the limitation, which, in our opinion, should be taken into account when applying such models, is their "individuality" and a proclivity for "aging" as mentioned by Akers (2007), Jones (2004) and Nigrini (2005). However, the practical application of the models belonging to the group described demonstrates the high efficiency at a level, close to 80% (Jones, 2004)) of their use in the RMMF assessment. According to the authors, the use of regression models of binary choice is justified when performing risk assessment procedures on the following stages: a) client risk profiling or further cooperation; b) risk assessment procedures and c) completion of the audit. In this sphere, their use will contribute to the RMMF identification and assessment at the level of financial statements as a whole.

Another regression model, proposed as a RMMF assessment method during the audit, gained its fame as a model of Jones (1991). Besides, there are modifications of Jones's model, used by auditors, which were described in Dechow *et al.* (1995). The basis for creating the model was based on the assumption, made by McNichols and Wilson, (YEAR+ reference) about the division of a company's expenses, depending on the accrual method, into discretionary and non-discretionary[1] (Dechow *et al.*, 1995). Jones's model estimates non-discretionary accruals *NDA* during the period under review (i.e. during the period when the earnings management was allegedly carried out). The model is as follows:

$$NDA_t = \alpha_1 \left(1/A_{t-1} \right) + \alpha_2 \left(\Delta REV_t \right) + \alpha_3 PPE_t ,$$

where A_{t-1} is the total amount of assets in the period t-1; ΔREV_t is the difference in income in the period t and in t-1, brought to total assets during t-1 period; PPE_t − are

[1]*Discretionary accruals are expenses that are not a prerequisite for carrying out the company's operations, and therefore taken into account by way of professional judgment of a reporting accountant. Non-discretionary accruals are expenses that are a prerequisite for carrying out the company's operating activities (all expenses except discretionary ones) (authors' note).*

gross fixed assets in the period *t*, brought to total assets in the period *t*-1; α_1, α_2, α_3 are specific parameters of the company.

Company parameters α_1, α_2, α_3 are obtained by applying the Least Squares Method to the equation

$$TA_t = \alpha_1 \left(1/A_{t-1}\right) + \alpha_2 \left(\Delta REV_t\right) + \alpha_3 PPE_t + \nu_t ,$$

where TA_t are total accruals, brought to total assets in the period *t*-1, and ν_t is a random error.

Jones's (1991) model suggests that the company's revenues are non-discretionary. A company allows its revenue at the end of the year, but the cash flow, associated with this income, is not available. As a consequence, it calls into question the actual existence of the accrued income. Jones's model orthogonalizes accruals in relation to income and, as a result, achieves the discretionary component of accruals that shifts earnings management assessment to zero value.

In order to eliminate the alleged tendency of Jones's model to measure discretionary accruals with an error, when discretion is applied to income, a modification of the model is used in the audit. Within the modified Jones's model non-discretionary accruals are measured during the current period as in

$$NDA_t = \alpha_1 \left(1/A_{t-1}\right) + \alpha_2 \left(\Delta REV_t - \Delta REC_t\right) + \alpha_3 PPE_t ,$$

where ΔREC_t is the difference between the receivables in the period *t* and in *t*-1, brought to total assets in the period *t*-1.

The only adjustment in the modified Jones's model is that changes in income occur in response to changes in accounts receivable during the current period. The original model of Jones implicitly assumes that with incomes no discretion is carried out in the current period, or in the assessment period. The modified version of the model implicitly assumes that any changes in sales on credit are the result of manipulation of the income. This conclusion is based on the following reasoning: it is easier to manipulate earnings, exercising discretion in respect to proceeds from sales on credit, than in relation to sales revenue for cash. Testing of the modified model with random samples (Dechow *et al.,* 1995) showed a sufficient potential of such a test to detect income fraud.

Since the basis of Jones's model is the assumption about the non-discretionary character of a company's revenues, the presence of discretionary income is considered a factor that increases the probability of material misstatement in financial statements due to fraud. The auditors in their practice use the modified model. Since it is generally accepted that much of the financial statement fraud in any company aims at generating an optimistic view of the financial result, the given model, in our opinion, can be effectively used in performing RMMF assessment procedures at the financial statement level as a whole, as well as for RMMF identification, assessment and reduction at the preliminary level for groups of accounting income operations. We also state that Jones's model can be effectively used in the risk assessment on such assertions as "integrity" and "reference to a time period." The advantages of this model include a relative simplicity of calculating its value based on published information as well as its high efficiency, estimated in various studies at the level of 70-85%. The effectiveness of the model application, in our opinion, can be influenced by the complexity of individual customer parameters and a lack of clear RMMF assessment criteria. The results of the analysis carried out show that the model is useful on the stages of client risk profiling or for further cooperation, substantive procedures, and finalizing the audit.

Another model recommended for use in RMMF assessment procedures is the *F*-score model. The model is based on calculating the *F-score* indicator depending on a number of parameters, which include: financial performance, non-financial parameters, off-balance-sheet performance, market performance (Dechow *et al.*, 2011; Thalassinos *et al.*, 2012a; 2012b, 2013). The model uses the techniques of the above mentioned regression models of discrete choice. The dependent variable takes the value of 1 for companies, involved in manipulation of the statements, and 0 for others.

To assess the RMMF risks, the authors (Dechow *et al.*, 2011) specify three models for fraud detecting in financial statements. Model 1 includes only the financial performance values of companies, Model 2 - further non-financial and off-balance-sheet values, Model 3 - further market performance.

The explanatory variables within Model 1 are: change in non-cash net short-term assets; change in the value of accounts receivable; changes in capital investments; the proportion of intangible assets to total assets; changes in sales revenue for cash; a change in the return on assets; a number of active patents.

Model 2 includes all the explanatory variables of Model 1, and in addition to them, the following non-financial values: a radical change in the number of employees; the existence of active lease agreements.

Model 3 includes values of Model 2, as well as market performance: market-adjusted stock returns; adjusted market stock returns with a lag.

Dechow *et al.* (2011) put forward the following algorithm for calculating the *F-score*.

1. Calculation depends on the type of model used for estimating the coefficients. In particular, in this research we estimate the parameters of all three models and predicted values of the dependent variable.

2. The prognostic probability is calculated.
3. The absolute average value of probability, understood as the ratio of the number of companies with financial statement distortion to the total number of companies included in the sample, is calculated.
4. The *F-score*, understood as the ratio of the prognostic probability to the unconditional average value of the probability, is calculated.
5. At the final stage a normative analysis of the obtained values of the index is carried out, in compliance with the following intervals:
F-score ranging from 0 to 1 is a low, acceptable level of risk;
F-score ranging from 1 to 2.45 is a risk above normal;
F-score greater than 2.45 is a high level of risk.

The inventors of the *F-score* have proved that the probability of financial statement fraud increases during periods of significantly growing charges (revenues and (or) costs). They argue that such periods are characterized by distortion of sales data, unrealistically high expectations of the company shares value, off-balance-sheet financing through leasing, etc.

The potential use of non-financial parameters (hereinafter NFP) in the RMMF assessment, as described in Brazel (2009) and Ittner and Larcker (1998) shows that the dynamics of revenue and non-financial parameters, such as the number of employees, the number of visitors, the number of retail outlets and the distribution centers of companies, are correlated with each other in varying degrees. Therefore, one of the hallmarks of a high RMMF is the weak correlation of the dynamics of these parameters. Currently, the models, used in the audit, make it possible to analyze the relationship of the time series of integrated parameters of financial statements (balance sheets, total operating income, and operating expenses) with the NFP, such as production capacity in physical units, warehouse space, etc. The advantage of the NFP in RMMF assessment is giving many opportunities of their application to virtually all account balances, classes of operations and information disclosures in the context of virtually all existing assertions and their combinations.

An important condition for the use of models, containing non-financial parameters, in order to identify, assess and mitigate RMMF at the assertion level, is determining a one-to-one connection between a selected non-financial parameter with RMMF in the context of a given assertion. It is an essential restriction when using the NFP to assess RMMF, as the use of untested connections, that may seem logical according to the auditor's opinion, can lead to an incorrect RMMF assessment.

The applying of regression analysis (Enhbayaar and Tsolmon, 2015; Bell and Carcello, 2000; Yusof *et al.*, 2015) is a quite popular tool for contemporary researchers to conduct a quantitative auditory assessment of the RMMF. In their study, Bell and Carcello (2000) distinguish the following important factors: weak internal control; a fast company growth; profitability, untypical for the given industry during the financial period; giving excessive value to profit when assessing management; managers' evasive behavior when dealing with auditors; the company ownership structure. The authors demonstrated the advantage of their model as compared to the RMMF assessment, as carried out by practicing auditors on the basis on their professional judgment. In Yusof *et al.* (2015) regression analysis is used to test more than a dozen hypotheses, put forward with the help of experts. Both financial parameters and factors characterizing the internal environment of the company are applied. The research by Enhbayaar and Tsolmon (2015) summarizes, in particular, the international experience of building RMMF assessment models using Altman's *Z-score*.

3. Results

During the study, we conducted a comparative analysis of the above regression models in terms of their potential use in RMMF assessment. The results of the comparative analysis for four parameters are presented in Table 1.

Table 1. *The results of the comparative analysis of the applicability of regression models in the risk assessment procedures during audit*

Para meter	Models			
	M.Beneish, M.Roxas, S.Spatis	J.Jones	T.Bell, J.Carcello	Nonfinancial measures
1	Information availability for calculation, availability of a regulatory assessment scale, simplicity of calculation, high probability (75-85%) of RMMF identification	Information availability for calculation, availability of a regulatory assessment scale, simplicity of calculation, a high degree of RMMF assessment aggregation combined with the ability to assess it at a level of individual operation groups	The ability to use the model when assessing RMMF in different areas of audit, a combination of quantitative assessment with the auditor's judgment	Unlimited use for different assertions, the use of professional auditor's judgment in identifying significant relationships with NFM
2	The need for periodic revision of the explanatory variables, the need to take into account individual characteristics of each customer to improve the reliability of the	Models aiming at the financial results, as given in statements a limited use of RMMF assessment as a tool on the assertion level, the need to calculate the parameters of each individual customer,	Potentially high subjectivity of judgments concerning RMMF, ambiguity of the list of factors affecting the results of RMMF assessment	The need to test the significance of the relationship between financial and non-financial parameters, the human factor in the

	results of model calculation	the absence of unambiguous criteria for evaluating the results of calculation		application of professional judgment
3	Financial statements as a whole, statement elements, the values of which are involved in the calculation of explanatory variables	Financial statements as a whole, operation groups for recognition of revenues and expenses in the context of "integrity" and "assignment to the period"	Cash balances, operation groups and information disclosure in the context of all assertions	Cash balances, operation groups and information disclosure in the context of all assertions
4	Conducting customer risk profiling or further cooperation procedures, risk assessment procedures completed audit	Conducting customer risk profiling or further cooperation procedures, risk assessment procedures completed audit	Carrying out risk assessment procedures at the assertion level in relation to account balances and operation groups completed audit	Conducting customer risk profiling or further cooperation procedures, carrying out risk assessment procedures at the assertion level in relation to account balances and operation groups

***Note**. The numbers in the table show the comparison parameters: 1 − advantages of the model; 2 − disadvantages of the model; 3 − the level of risk assessment procedures, at which the model can be used; 4 − stages of audit, on which the model can be used.*
***Abbreviations in the table stand for:** NFM − nonfinancial measures; RMMF − the risks of material misstatement resulting from financial statement fraud.*

4. Conclusion

The results of the study lead us the following conclusions:
− The regression models of RMMF assessment analyzed can be widely used by auditors to conduct risk assessment procedures when performing tasks that inspire confidence. This is facilitated by the simplicity of calculation and invariance of coefficient computation within the majority of the described models, as well as by the use of binary functions that allow you to assess the likelihood of the audited financial statements having parameters that reveal "aggressive" interference of the accountants.

− Regression analysis models have a wide range of application as tools for RMMF assessment at various levels (statements as a whole, individual elements and assertions) and stages of the audit (customer risk profiling / further cooperation, closing procedures).
− Having enough "improving" models, with their authors contradicting each other and / or improving earlier projects at the same time, makes us assume that their practical application should be carried out with a number of limitations. These restrictions, in our opinion, may include sectoral affiliation, the scale of a company, special features of accounting regulations and corporate administration, business practices of the country, where the activity is going on, etc.

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