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**Application of Beneish and Roxas M-Score Models to Detect Financial Statement Fraud: Evidence from Russia**

**Introduction**

Currently annual financial report (balance sheet and income statement) is an important source of information for stakeholders. However before making financial decisions based on this available data it seems reasonable to verify that the figures in the reports are not falsified.

It is worth stressing that now falsification of the financial statement is one of the most wide-spread types of cheating in Russia: about 20 % of the companies engaged in economic crime have provided falsified financial statement (Draft on the Nationwide Survey “Practice of Fighting the Corporate Fraud” Final Report, 2014). Moreover, according to the Report to the Nations financial statement fraud leads to the most significant losses in comparison with other types of cheating (Report to the Nations on occupational fraud and abuse, 2014). In connection with such a trend it is essential for stakeholders to employ effective methods of financial fraud detection.

Nowadays Institute of External Auditors remains one of the most reliable tools which identify financial statement manipulation. However not all Russian companies are required by law to be audited. At the same time the development of initiative audit is rather limited because of significant costs. For instance, Kizilov A. reveals that average revenue per the client received by auditors is about 1000000 rubles (Kizilov A., 2015). Furthermore, audit takes time, and this, in turn, affects timeliness of financial decision-making. All these facts point to the need for a new tool which enables stakeholders to identify fraud risks quickly and inexpensively.

It was found that ideas of many researchers boil down to the development of the mathematical models determining whether a company provides misleading information about assets, revenue, costs and liabilities. To detect falsifications researchers create the specific integrated index (M- Score) calculated on the basis of the specific financial ratios.

**Literature review**

The vast majority of authors (Harrington C., 2005; Roxas M., 2011; Normah O., 2014; Arshad R., 2015; Tarjo, 2015) indicate the importance of the integrated indexes which would have signaled that financial statement fraud risks are high, but Beneish research can be considered as fundamental in this field (Beneish M., 1999). He used 8 financial ratios to develop probit-model and, as a result, found the interrelation between them and the facts of fraudulent financial reporting. Beneish included in the model days' sales in receivable index (DSRI), gross margin index (GMI); asset quality index (AQI), sales growth index (SGI), depreciation index (DEPI), sales and administrative expenses index (SGAI), leverage index (LVGI) and total accruals to total assets (TATA). He combined these variables together to achieve M-Score for the company:

M-Score = -4,840 + 0,920\*DSRI + 0,528\*GMI + 0,040\*AQI + 0,892\*SGI + 0,115\*DEPI-0,172\*SGAI + 4,679\* TATA- 0,327\*LVGI.

To calculate the benchmark (threshold) for M-Score Beneish used the average of included financial ratios for US companies. It was found that M-Score less than -2,22 suggests that the company will not be a manipulator whereas M-Score greater than -2,22 signals that the company is likely to be engaged in financial statement fraud.

In 2011 M. Roxas changed the model by excluding SGAI, LVGI and TATA and reassessed it:

M-Score = -6,065+ 0,823 \*DSRI + 0,906 \*GMI + 0,593 \*AQI + 0,717 \*SGI + 0,107\*DEPI.

New benchmark for M-Score is -2,76 (Roxas M, 2011).

The effectiveness of these instruments is really high because they correctly identify more than 70% and 80% of manipulators and non-manipulators respectively in USA (Beneish M., 1999; Roxas M, 2011). However the application of M-Score method in Russia is debatable because of the differences in accounting and reporting principles in USA and Russia.

**Problem statement and research hypotheses**

The primary aim of the present study is to identify whether it is possible to distinguish fraudulent from non-fraudulent financial statement reporting in Russia with the help of Beneish and Roxas models.

Hypothesis 1: Employing Beneish model we can distinguish fraudulent from non-fraudulent financial statement reporting in Russia.

Hypothesis 2: Employing Roxas model we can distinguish fraudulent from non-fraudulent financial statement reporting in Russia.

Hypothesis 3: The performance of both Beneish and Roxas models increases if benchmarks will be calculated on the Russian companies’ data.

**Methods and results**

To check the hypotheses about the ability of Roxas and Beneish models to detect financial statement fraud in Russian companies we collect the data on the financial statements submitted under Russian Accounting Standards.

Our sample consists of sixty Russian firms operating in agriculture, manufacture, wholesale trade and construction industries. We extract a sample of fraudulent firms from two sources: RosPravosudie (https://rospravosudie.com/) and Unified solutions database of the Russian Federation General Jurisdiction Courts (<http://xn--90afdbaav0bd1afy6eub5d.xn--p1ai/>). These sources provide the data on lawsuits under section 176.1 of the Russian Criminal Code. If the executive of the company is convicted of providing the bank or other lender false information about the companies’ financial position we include this company in the sample.

When we collect information about non-fraudulent firms we not only check them through judgments data base but also find positive audit reports to ensure that companies are not engaged in creative accounting. So we have compiled a sample comprising 28 fraudulent and 32 non-fraudulent firms.

The data (balance sheets, income statement, and industry) over the period of 2006-2008 years was obtained from FIRA and SPARK dataset. Basing on the information about current and non-current assets, gross profit, turnover, operating costs and liabilities we calculated the financial ratios included in Beneish and Roxas models.

Lack of data on depreciation made us to exclude TATA and DEPI. We believe that this doesn’t cause deterioration of model performance because Russian companies avoid revising useful life of assets and depreciation method. After that we calculated the new benchmarks for M-Score Beneish and M-Score Roxas and they were about -2,424 and -2,965 respectively.

Then we compute integral indexes (M-Scores) for both Beneish and Roxas models and compare the results for each company of the sample with the benchmark. After that we counted the number of cases in which the fraud status was determined incorrectly: the manipulators are not recognized as fraudsters, and vice versa.

It was revealed that the Beneish model correctly predicted 37 of the 60 companies’ fraud status. So accuracy level is 62%. In comparison, performance of Roxas model is lower: thus, only in 35 cases fraud status was identified correctly. It is worth stressing that more than 55% of non-manipulators were recognized as fraudsters.

Then we revised benchmarks for models, basing on average of included financial ratios for Russian companies. As a result, performance of models increased: new accuracy level reached 68% and 70% for Beneish and Roxas models respectively. Number of incorrect predictions for non-fraudulent companies dropped significantly. At the same time error rate for fraudsters increased by 20% and it is impossible to ignore this problem because greater risk lies in the fact that we recognize fraudsters as trustworthy companies. This, in turn, proves that Beneish and Roxas models need to be improved. In order to provide Russian stakeholders with effective methods of financial statement fraud detection it seems reasonable to specify variables in models taking into account features of business practices, reporting and accounting standards in Russia.