ATLANTIS PRESS
Advances in Economics, Business and Management Research, volume 79
International Scientific Conference "Far East Con" (ISCFEC 2019)

The Evaluation of Applicability of Known Models for Identification of Financial Inconsistencies in Conditions of Russian Economic Realities

Gudova M.
Financial University under the Government of the Russian Federation, 125993 Moscow, Russia
e-mail: GudovaMR@gmail.com

***Abstract*—Modern economic tendencies coupled with political tension and increasing share of shadow economy are pointing to the need of the new decision making support tools to further mitigate negative influences both at the companies' and at state's levels. The introduction of methods for identification of financial inconsistencies may be one of such tools. The goal of this research is the evaluation of applicability to the Russian economic reality of the most efficient and adaptive models for identification of financial inconsistencies by testing them using data from Russian companies that were found guilty in committing financial inconsistencies since 2007 until 2016 by the Russian law. The results of the research indicate that those methods are ineffective when implemented to Russian economic realities due to specific of the state economy and the nature of financial inconsistencies of Russian companies.**

Keywords—financial inconsistencies, irregularities, corporate fraud, financial consistency, economic growth.

I. The Essence of Financial Inconsistencies and Tools for Their Identification

A. Introduction

Modern economic tendencies are negative, such as [17]: depreciation of the bonds of Italian banks increases risk of financial panic in the countries of the European Union; increase of the China's state debt despite the orientation of the policy on economic growth keeps it's economy unstable; uncertainty in decisions made by the current US government creates risks of increase of the US federal budget's deficit and of further decrease of interest rates; the increase of the standard rate of VAT in Russia creates conditions for escalation of inflation which when coupled with decrease of overall demand and sanctions against Russian Federation and inefficient governing policy confirms forecasts of the IMF about decrease in real GDP in 2018 and 2019 [21]. In that situation such events as financial violations, corporate frauds and other negative influences of the economic life, which are a part of the larger phenomenon of financial inconsistencies, have a destructive influence on the economies of countries.

Phenomena such as these lead to incorrect determination of scale of the economics, formation of inadequate for real economy conditions state policy, slowdown of economy growth and decrease of financial stability of companies.

Financial inconsistencies are a system of self-developing relations directed at achieving financial or other gains by intentional or unintentional providing of false data or omission of facts or accounting data [6]. It is important to note that financial inconsistencies are deviations of norm in financial and economic activities of companies.

According to the data provided by PricewaterhouseCoopers (PwC) [18], Association of Certified Fraud Examiners (ACFE) [20] agencies in 2017 there is a decrease in percentage of respondents that confirm the fact of encountering financial inconsistencies.

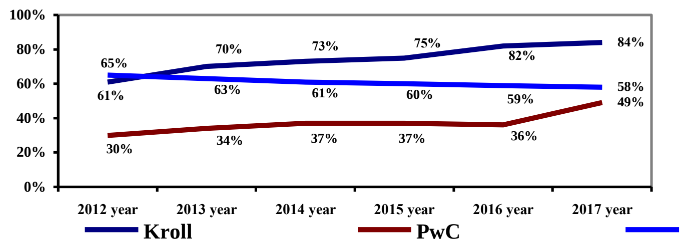

Fig. 1. Correlation of percentage of respondents of consulting, audit and analytical agencies Kroll [19], PwC, ACFE, that have encountered financial inconsistencies.

On the other hand Kroll agency [19] has stated that the amount of respondents encountering financial inconsistencies is increasing. One of the possible reasons why those results are so contradicting is the lack of tools that would allow precise identification of financial inconsistencies.

Despite noted decrease in the share of respondents that have confirmed the fact of encountering financial inconsistencies ACFE verifies that the amount of yearly losses suffered by companies due to financial inconsistencies is preserved at level of 5.0 percent of their annual income. At the same time average damage to companies caused by financial inconsistencies in Russia and Asia is around 150 thousand dollars annually [20].

The data confirms that the problem of identification of financial inconsistencies is the issue of the day as never before and the tools to precisely identify them are highly required.

The goal of this research is to test different methods for identification of financial inconsistencies on data provided by Russian companies.

B. Overview of the Toolkit of Identification of Financial Inconsistencies and Research Hypothesis

There is a lot of research regarding development of new methods for identification of financial inconsistencies. The first efficient models [Beneish M., 1999] [3] for identification of financial inconsistencies was oriented on violations committed by companies while they were accommodating their shares on the stocks and is based on financial factors [Persons, 1995] [13]. Due to their rapid development of methods for identification of financial inconsistencies achieved much higher precision by incorporating of mathematical and modeling methods [Kirkos, 2007] [11], [Cecchini, 2010] [4]. Another reason for the increase in precision of models for identification of financial inconsistencies is caused by usage of not only financial factors but also non-financial which can be proved by increase of precision of models where non-financial factors are also being considered [J. Kim, Bok Baik, Sungzoon Cho, 2016] [10].

It is important to note that some of the most effective models, for example Cecchini model [4], require data with limited access which is not provided even to government agencies. That’s why one of the most challenging tasks is to find a method that will allow us to identify financial inconsistencies with high precision without requiring of such data.

Also it should be pointed out that the methods for identification of financial inconsistencies such as methods developed by Beneish [2], Spathis [15], Persons [13] are heavily based on the specifics of certain companies and countries that does not allow to guarantee the applicability of such models to Russian economic realities.

II. Approbation of the Base Models for Identification of Financial Inconsistencies

A. Empirical Research Base

In order to identify the most adequate and efficient method for identification of financial inconsistencies that is equally applicable to Russian economic reality the data of 698 Russian companies, 348 of which are found guilty in committing financial inconsistencies by the Russian law since 2007 until 2016, is used. And for the sample of companies that have not committed such crimes were chosen companies that are similar to those that are found guilty by organization form. It is noteworthy that healthy companies were required to maintain net income and equity during past seven years and also were not charged in committing financial inconsistencies.

A. Characteristics of the Applied Models

In this research 3 methods for identification of financial inconsistencies were chosen to identify financial inconsistencies of the Russian companies. The chosen models appear to be the most effective and applicable taking into account the specifics of the Russian Accounting standards.

The evaluation of quality of the applied methods was implemented through comparing indicators of predictive power of those methods (shares of correct classification of companies with inconsistencies and without).

TABLE I. Models for identification of financial inconsistencies

Authors of model	Variables	Claimed accuracy of base model
Ch. Spathis [15]	Debt / Equity Sales / Total assets Net profit / Sales Accounts receivable / Sales Net profit / Total assets Working capital / Total assets Gross profit / Total assets Inventory / Sales Total debt / Total assets Log Total assets	83,5 % – 88,5 %
R. Kanapickiene & Z. Grundiene [9]	Inventory / Total assets Sales / Fixed assets Total liabilities / Total assets Cash / Current liabilities	84,8%
H. Dalnial, A. Kamaluddin, Z. M. Sanusi & K. S. Khairuddin [5]	Square/Log (Total debt / Total equity) Log (Receivable / Revenue) Log Z- score [1]	72,3%

III. Approbation and Analysis of Empiric Results of Models for Identification of Financial Inconsistencies of Companies on Data of Russian Companies

According to the methodology of calculations the results of application of discussed models on data of the sample were evaluated.

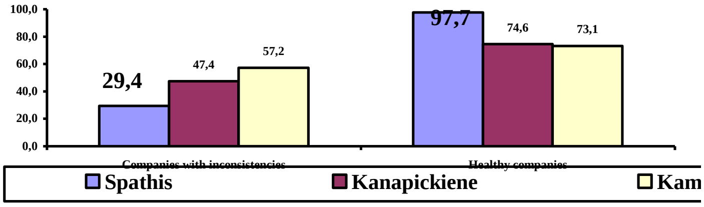

Fig. 2. Correlation of percentage of correctly-classified Russian companies by models for Ch. Spathis, R. Kanapickiene, A. Kamaluddin, %.

The results of test showed that the models are achieving low accuracy, to be more exact 63,5% for Ch. Spathis, 61% for R. Kanapickiene, 65,4% for A. Kamaluddin. The obtained data of the models accuracies insufficient to effectively identify financial inconsistencies of companies in the conditions of the Russian economy. Acknowledgment of the foregoing is also the low share of correctly-classified Russian companies with financial inconsistencies by all approbated models.

IV. Conclusion

In this research three of the most efficient and adaptive methods for identification of financial inconsistencies of companies were tested on the data of 698 Russian companies

The results have shown that those models are inefficient when are implemented in the Russian economic reality (the best accuracy achieved is 65,4 %). One of the main reasons behind that are specifics of the Russian economy, accounting system and as a result differentiation of the financial inconsistencies in Russia compared to the rest of the world.

The possible solution to the problem of efficient and well-timed identification of financial inconsistencies of Russian companies may be the development of a new method for identification of financial inconsistencies with specifications of Russian economic reality in mind. Moreover the implantation of non-financial factor during the development of the model for Russian companies could greatly increase the overall accuracy which was proven earlier in research made by J. Kim, Bok Baik, Sungzoon Cho (2016) [10].

References

[1] Altman, E., Haldeman, R., Narayanan, P. ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations. Journal of Banking and Finance 1, 29-54 (1977).

[2] Beneish M.D. Detecting GAAP violation: implications for assessing earnings management among firms with extreme financial performance. Journal of Accounting and Public Policy 16(3), 271-309 (1997).

[3] Beneish M.D. The detecting of earning manipulation. Financial Analysts Journal 55(5), 24-36 (1999).

[4] Cecchini, M., Aytug, H., Koehler, G., and Pathak, P. Detecting Management Fraud in Public Companies. Management Science 56(7), 1146-1160 (2010).

[5] Dalnial, H., Kamaluddin, A., Sanusi, Z., Khairuddin, K. Accountability in financial reporting: detecting fraudulent firms. Procedia - Social and Behavioral Sciences 145, 61–69 (2014).

[6] Gudova M.R. Financial inconsistencies in companies: the essence of the concept, the formation of a unified approach to this phenomenon. AKSOR Bulletin 2/2017(42), 218-223 (2017).

[7] Gupta, R., Gill, N.S. A Data Mining Framework for Prevention and Detection of Financial Statement Fraud. International Journal of Computer Applications (0975 – 8887) 50(8), 7-14 (2012)

[8] Feroz E., Kwon, T., Pastena, V., Park, K. International Journal of Intelligent Systems in Accounting, Finance & Management 9, 145-157 (2000).

[9] Kanapickiene, R, Grundiene, Z. The Model for Fraud Detection in Financial Statements by Means of Financial Ratios. Procedia - Social and Behavioral Sciences 213, 321–327 (2015).

[10] Kim, J., Baik, B., Cho, S. Detecting financial misstatements with fraud intention using multi-class cost-sensitive learning. Expert Systems with Applications 62, 32–43(2016).

[11] Kirkos E., Spathis C., Manolopoulos Y. Data mining techniques for the detection of fraudulent financial statements. Expert Systems with Applications 32 (4), 995–1003 (2007).

[12] Pashtova, L. Risk management and information use with a view of decrease in enterprise losses. The Journal of North Ossetian State University 4, 281-286 (2012).

[13] Persons O.S. Using financial statement data to identify factors associated with fraudulent financial reporting. Journal of Applied Business Research 11(3), 38-46 (1995).

[14] Ravisankar, P., Ravi, V., Raghava, R.G., Bose, I. Detection of financial statement fraud and feature selection using data mining techniques. Decision Support Systems 50, 491-500 (2011).

[15] Spathis C. Detecting false financial statements using published data: some evidence from Greece. Managerial Auditing Journal 17(4), 179–191 (2002).

[16] Watson, H. J., Wixom, B. H. The Current State of Business Intelligence. IEEE Computer 40 (9), 96-99 (2007).

[17] Fortune Homepage, http://www.fortune.com/2017/01/01/economy-2017/, last accessed 2018/02/18.

[18] Global Economic Crime and Fraud Survey 2018 Homepage, https://www.pwc.com/gx/en/forensics/global-economic-crime-and-fraud-survey-2018.pdf, last accessed 2018/03/01.

[19] Global Fraud & Risk Report. 10th Annual edition-2017/18 Homepage, https://www.kroll.com/en-us, last accessed 2018/03/01.

[20] Report to the nations: 2018 Global study on occupational fraud and abuse. Association of Certified Fraud Examiners Homepage, http://www.acfe.com/report-to-the-nations/2018, last accessed 2018/03/01.

[21] Review of Global Politics and Economy in 2017 and Outlook for 2018 Homepage, https://www.mitsui.com/mgssi/en/report/detail/__icsFiles/afieldfile/2018/01/05/171214_e.pdf, last accessed 2018/02/18.

[22] Russian Economic Crime Survey 2016 Homepage, https://www.pwc.ru/ru/assets/recs-ru-final.pdf, last accessed 2018/02/18.