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Procedia
Social and Behavioral Sciences

Procedia - Social and Behavioral Sciences 213 (2015) 321 – 327

20th International Scientific Conference Economics and Management - 2015 (ICEM-2015)

The Model of Fraud Detection in Financial Statements by Means of Financial Ratios

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Abstract

Analysis of financial ratios is one of those simple methods to identify frauds. Theoretical survey revealed that, in scientific literature, financial ratios are analysed in order to designate which ratios of the financial statements are the most sensitive in relation with the motifs of executive managers and employees of companies to commit frauds.
Empirical study included the analysis of the following: 1) 40 sets of fraudulent financial statements and 2) 125 sets of non-fraudulent financial statements (unconditional audit report was issued for the sets of financial statements of these companies). The aim of the research is to distinguish financial ratios, the values of which could indicate the fraud in financial statements. Moreover, the logistic regression model of fraud detection in financial statements has been developed. The research is unique for being the first empirical study of its type in Lithuania.

Peer-review under responsibility of Kaunas University of Technology, School of Economics and Business

Keywords: Fraud detection; Financial statements; Financial ratios.

Introduction

Financial statements are drawn to present fair information about the financial position, operating performance and cash flows of the company. The reason for that is that the owners of companies, investors, creditors, governmental institutions make decisions regarding the development of the company on the basis of the information provided in financial statements. However, according to the international standards on auditing, management is in a unique position to perpetrate fraud because of management's ability to manipulate accounting records and prepare

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Peer-review under responsibility of Kaunas University of Technology, School of Economics and Business
doi:10.1016/j.sbspro.2015.11.545

fraudulent financial statements by overriding controls that otherwise appear to be operating effectively. Therefore, it is essential to analyse the different methods of fraud detection in financial statements.

In accounting and audit works the detection of fraud in the financial statements in most cases is analysed from the perspective of audit – fraud risk factors are identified and fraud risk is assessed. In interdisciplinary scientific works of informatics, accounting and audit the analysis of models that could help detect fraud in the financial statements very complex and oriented towards the audit process. The problem of fraud in financial statements is also researched in Lithuanian scholarly works on accounting and auditing: Mackevičius, Bartaška (2003), Lakis (2007, 2008, 2009, 2011), Mackevičius (2007), Kanapickienė (2008, 2009), Mackevičius & Kazlauskienė (2009), Kuktaitė & Kustienė (2012), Mackevičius & Giriūnas (2013). This notwithstanding, issues of fraud detection in the financial statements are usually analysed in the context of the audit.

It is worth mentioning that models designed for the external users of financial statements are analysed in scientific papers insufficiently, e.g., for investors, creditors who examine financial statements for fraud. Analysis of financial ratios is one of those simple methods to identify frauds. This relevant issue is dealt by foreign scientists, but such studies are insufficient in Lithuania. The aim of the research is to develop the model of fraud detection in financial statements by means of financial ratios (case of Lithuania).

The theoretical research investigates frauds in financial statements and possibilities to detect frauds by means of financial ratios. The analytical study deals with fraudulent and non-fraudulent financial statements of surveyed companies. During the study 1) financial ratios exhibiting information about fraud in the financial statements were selected by applying statistical methods; 2) models of logistic regression were investigated with regard to possibility of their use for fraud detection and the most appropriate model for fraud detection was selected.

1. The use of financial ratios in fraud detection

In research studies (Feroz et al., 1991; Stice et al., 1991; Persons, 1995; Wells, 1997; Fanning & Cogger, 1998; Beneish, 1999; Spathis et al., 2002; Lenard & Alam, 2009; Ravisankar et al., 2011) the analysis of ratios is chosen as one of the methods to determine fraud. After theoretical research, the financial statement ratios used in scientific literature were grouped into 5 groups and subgroups of financial statement ratios (Table 1). This confirms that different scholars choose different financial ratios for fraud investigation.

Financial difficulties may be motivation for managers to engage in fraudulent activities. According to Fanning & Cogger (1998), Kirkos et el. (2007), Ravisankar et al. (2011), the higher levels of debt may increase the probability of the fraudulent financial statements too. The following ratios are mostly used in research works with regard to fraud detection: the total debt to total assets (TD/TA) ratio (Kirkos et al., 2007; Gaganis, 2009; Sen & Terzi, 2012; Dalnial et al., 2014) or the total liabilities to total assets (TL/TA) ratio (Lenard & Alam, 2009); the total debt to equity (TD/Eq) ratio (Spathis et al., 2002; Kirkos et al., 2007; Dalnial et al., 2014). Lower liquidity may be an incentive for managers to engage in fraudulent financial statements. Mostly liquidity is measured by the working capital to total assets (WC/TA), the current assets to current liabilities (CA/CL) ratio (Lenard & Alam, 2009; Ravisankar et al., 2011).

According to Song et al. (2014), Stice et al. (1991), another fraud motivation for the company managers is to keep growing. In order to find out whether the company kept growing, researchers used activity, profitability, asset composition ratios to detect fraud: the sales to total assets (SAL/TA) ratio, the net profit to sales (NP/SAL) ratio, the net profit to total assets ratio (ROA), the current assets to total assets (CA/TA) ratio were frequently used. Kirkos et al. (2007) claim, that the gross margin is also prone to manipulation. The authors used the following ratios for fraud detection: the Gross profit to Sales (GP/SAL) ratio, the Gross profit to Total Assets (GP/TA) ratio.

According to Stice et al. (1991), Persons (1995), Kaminski et al. (2004), Kirkos et al. (2007), Perols (2011), the inventories, accounts receivable are the financial statement variables which permit a subjective estimation. Thus the ratios used to determine such fraudulent statements are the inventories to sales (INV/SAL) ratio, the inventories to total assets (INV/TA) ratio, the accounts receivable to sales (REC/SAL) ratio.

The literary references indicate that usage of the financial ratios for determining the fraudulent statements of financial reports is a convenient and straightforward means. However, the problem of interpreting the result interpretation arises, i.e. what value of financial ratio indicates that the reports are fraudulent.

2. Methodology of research

Data collection. Research was carried out by analysing 40 fraudulent (experimental group) financial statements and 125 non-fraudulent (control group) financial statements. Numerical values of the items of non-fraudulent financial statements are required in order to determine differences between fraudulent and non-fraudulent financial statements. Investigation period: 1998-2009.

Performance of research. In the first empirical stage of research the aim was to test all the relative financial ratios, the analysis of which was carried out in the theoretical part and which are used in the fraud detection determination. In total 51 financial ratios are analysed in the research. Each financial ratio is examined in the fraudulent and non-fraudulent financial statements.

Before choosing a statistical test, it is necessary to verify that data are drawn from a normally-distributed population. The main tests for the assessment of normality are Kolmogorov-Smirnov (K-S) test. If the results of the Kolmogorov-Smirnov test are significant ($p < \alpha$, there α – level of significance ($\alpha = 0.05$)), the data is from a non-normally distributed population.

If the assumption of normality has been violated, we use the Mann-Whitney U test. The null hypothesis H_0 is drawn: the distributions of financial ratio in the fraudulent and non-fraudulent financial statements are equal. H_0 is rejected, distributions of financial ratio are not equal if $p < \alpha$ ($\alpha = 0.05$).

If the assumption of normality is valid, we use the t-test. Firstly the equality of variances is evaluated using Levene's Test. Then the hypothesis of equality of averages is verified. Hypotheses for independent two-sample t-test: *Null hypothesis H_0:* financial ratio means do not differ in fraudulent and non-fraudulent financial statements. The decision is made based on the following provisions: 1) H_0 is rejected, averages are not equal, if $p < \alpha$; 2) H_0 is not rejected, averages do not differ, if $p \geq \alpha$ ($\alpha = 0.05$).

The possibility to apply the models of logistic regression for determining the fraudulent statements are investigated further. The models of logistic regression for determining the fraudulent statements have been applied by Perols (2011), Ravsankar et al. (2011), Leonard (2012). The investigated versions of model formation are as follows: 1) all selected independent variables are included in the model 2) firstly, applying the forward methods, the constants are set, after that, the independent variables having a strong correlation with a dependant variable are gradually included.

3. Empirical Results and discussion

Selection of financial ratios. The results of the Kolmogorov-Smirnov test have reported that the six financial ratios come from a normally-distributed population. Therefore, these ratios are explored with the t-test. Other ratios are explored with the Mann Whitney U test. The analysis of research results leads to the following conclusion: after the analysis of fraud-sensitive ratios presented in research works, it was determined that 51 of investigated fraud-sensitive ratios 32 proved to be efficient in Lithuanian companies. The following financial statements indicate the presence of fraud in financial statements (Table 1):

1a) Profitability ratios (Return of sales): the gross profit to sales (GP/SAL), the operating profit to sales (OP/SAL) ratios. Meanwhile, such ratios as the EBIT to sales (EBIT/SAL), the net profit to sales (NP/SAL) do not differ statistically in fraudulent and non-fraudulent statements, whereas the net profit to gross profit (NP/GP) ratio indicate the fraud. It shows that sales, cost of sales or operating expenses, which are not typical of usual business, are shown in financial statements.

1b) Profitability ratios (Return of Investment): the Gross profit to Total assets (GP/TA), the EBT to equity (EBT/Eq), the net profit to equity (ROE) ratios.

2) Liquidity ratios: the inventories to current liabilities (INV/CL), the cash to total liabilities (CACH/TL), the cash to current liabilities (CACH/CL) ratios.

3) Solvency ratios: All ratios of this group (except for the total liabilities to equity (TL/Eq) ratio) show statistically significant differences in fraudulent and non-fraudulent financial statements.

Table 1. Testing results of financial ratios

Financial ratio		Sig.[0]	Sig.[1,2]	Financial ratio		Sig.[0]	Sig.[1,2]
1a. Profitability ratios (Return of sales)							
Gross profit / Sales	GP/SAL	0,000	0,030[1]	Total liabilities / Equity	TL/Eq	0.000	0.168[1]
Operating profit / Sales	OP/SAL	0,000	0,043[1]	Total debt / Equity	TD/Eq	0.000	0.000[1]
EBIT / Sales	EBIT/SAL	0.000	0,087[1]	Long term debt / Equity	LD/Eq	0.000	0.000[1]
EBT / Sales	EBT/SAL	0.000	0.056[1]	Fixed assets / Long term Liabilities	FA/LD	0.000	0.000[1]
Net profit / Sales	NP/SAL	0.000	0.089[1]				
Net profit / Gross profit	NP/GP	0.000	0.020[1]	*4. Activity ratios*			
				Inventories / Sales	INV/SAL	0.000	0.060[1]
1b. Profitability ratios (Return of investment)				Cost of sales / Inventories	CS/INV	0.000	0.275[1]
Gross profit / Total assets	GP/TA	0.000	0.000[1]	Accounts receivable / Sales	REC/SAL	0.000	0.001[1]
EBIT / Total assets	EBIT/TA	0.000	0.409[1]	Sales / Fixed assets	SAL/FA	0.000	0.000[1]
EBT / Total assets	EBT/TA	0.000	0.822[1]	Sales / Total assets	SAL/TA	0.000	0.000[1]
Net profit / Total assets	ROA	0.000	0.903[1]	Sales / Equity	SAL/Eq	0.000	0.001[1]
EBT / Fixed assets	EBT/FA	0.000	0.245[1]	Sales / Total debt	SAL/TD	0.000	0.000[1]
Net profit / Fixed assets	NP/FA	0.000	0.240[1]	Cost of sales / Sales	CS/SAL	0.000	0.030[1]
EBT / Equity	EBT/Eq	0.000	0.021[1]	Operating expenses / Sales	OEXP/SAL	0.000	0.003[1]
Net profit / Equity	ROE	0.000	0.013[1]				
EBT / Current liabilities	EBIT/CL	0.000	0.253[1]	*5a. Structure ratios (Total assets structure ratios)*			
Retained earnings / Net profit	RE/NP	0.000	0.538[1]	Fixed assets / Total assets	FA/TA	0.200	0.000[2]
				Current assets / Total assets	CA/TA	0.200	0.000[2]
2. Liquidity ratios				(Inventories + Accounts receivable) / Total assets	INVREC/TA	0.200	0.000[2]
Current assets / Current liabilities	CA/CL	0.000	0.738[1]				
(Current assets – Inventories) / Current liabilities	(CA-INV)/CL	0,000	0,088[1]	Inventories / Total assets	INV/TA	0.000	0.000[1]
Inventories / Current liabilities	INV/CL	0,000	0,024[1]	Accounts receivable / Total assets	REC/TA	0.000	0.694[1]
Cash / Total liabilities	CACH/TL	0.000	0.004[1]	Cash / Total assets	CASH/TA	0.000	0.000[1]
Cash / Current liabilities	CACH/CL	0.000	0.038[1]				
Working capital / Total assets	WC/TA	0.002	0.719[1]	*5b. Structure ratios (Current assets structure ratios)*			
				Inventories / Current assets	INV/CA	0.001	0.009[1]
3. Solvency ratios				Cash / Current assets	CASH/CA	0.000	0.005[1]
Total liabilities / Total assets	TL/TA	0.200	0.000[2]				
Total debt / Total assets	TD/TA	0.000	0.000[1]	*5c. Structure ratios (Property structure ratios)*			
Long term debt / Total assets	LD/TA	0.000	0.000[1]	Retained earnings / Total assets	RE/TA	0.000	0.279[1]
Current liabilities / Total assets	CL/TA	0.200	0.000[2]	Retained earnings / Equity	RE/Eq	0.000	0.053[1]
Equity / Total assets	Eq/TA	0.200	0.001[2]	Current liabilities / Total liabilities	CL/TL	0.000	0.002[1]

Sig.[0] – Kolmogorov-Smirnov test p-value (significant at the 5% level); Sig.[2] – Mann-Whitney U p-value (significant at the 5% level); Sig.[2] – t-test p-value (significant at the 5% level)

4) Activity ratios: All ratios of this group (except for the inventories to sales (INV/SAL), the cost of sales to inventories (CS/INV) ratios, i.e., ratios defining inventory turns) show statistically significant differences in fraudulent and non-fraudulent financial statements.

5a) Structure ratios (Total assets structure ratios): All ratios of this group (except for the accounts receivable to total assets (REC/TA) ratio) show statistically significant differences in fraudulent and non-fraudulent financial statements.

5b) Structure ratios (Current assets structure ratios). Two ratios of this group were investigated: the inventories to current assets (INV/CA), the cash to current assets (CASH/CA) ratios. They show statistically significant differences in fraudulent and non-fraudulent financial statements. Interestingly, inventory structure is different both in total assets and in current assets of the company.

5c) Structure ratios (Property structure ratios): Ratios defining the share of retained earnings in total assets or property is not a statistically different ratio. Meanwhile, the Current liabilities to Total liabilities (CL/TL) ratio differ significantly.

Logistic regression model of fraud detection in financial statements. Logistic regression was used in creation of fraud classification model. During first stage, the following was included in the model financial ratios that show statistically significant differences in fraudulent and non-fraudulent financial statements. It was determined that multicollinearity problem exists in such models. Therefore, these models cannot be used and they have to be improved. During the second stage of research, the forward method was applied, as initially the constants are determined and later independent variables are gradually included into the models, i.e., financial statements with a strong correlation relationship to the dependent variable. The development of model is presented in Table 2.

Table 2. Logistic regression models of fraud detection in financial statements

	Model 1			Model 2			Model 3		
	Coefficients, Wald (p-value)**			Coefficients, Wald (p-value)**			Coefficients, Wald (p-value)**		
Net profit / Equity				0.703	1.858	(0.173)			
Inventories / Current liabilities	1.109	7.360	(0.007)	1.228	8.465	(0.004)			
Cash / Current liabilities							1.936	6.402	(0.011)
Total liabilities / Total assets	5.242	18.136	(0.000)	5.619	18.198	(0.000)	4.766	14.604	(0.000)
Sales / Fixed assets							0.029	4.953	(0.026)
Current assets / Total assets	3.048	9.033	(0.003)	2.722	6.614	(0.010)			
Inventories / Total assets							4.263	12.473	(0.000)
Cash / Current assets	5.104	8.003	(0.005)	5.832	9.299	(0.002)			
Constant	-7.279	35.522	(0.000)	-7.578	35.123	(0.000)	-5.768	34.148	(0.000)
The percentage of the model's correctly classified non-fraudulent cases			92.8			92.8			94.4
The percentage of the model's correctly classified fraudulent cases			47.5			52.5			55.0
The total percentage of the model's correctly classified cases			81.8			83.0			84.8
Chi-square p-value			0.000			0.000			0.000
Cox & Snell R Square			0.274			0.294			0.303
Nagelkerke R Square			0.409			0.438			0.452
Hosmer and Lemeshow p-value			0.490			0.948			0.541

**significant at the 5% level

The model is considered to be appropriate when Chi square criterion p-value < 0.05; Cox & Snell R Square, Nagelkerke R Square > 0.2; Hosmer-Lemeshow's chi square p-value > 0.05. Statistically significant variables should be included in the model, i.e., p values of Wald's p-value < 0.05. With regard to these criteria, the Model 3 formulation shall be considered to be the best. The total percentage of the model's correctly classified cases is 84.8%.

Under this logistic regression model, the probability of fraud is calculated as:

$$P = 1/(1 + e^{5.768 - 4.263 \times \mathrm{INV/TA} - 0.029 \times \mathrm{SAL/FA} - 4.766 \times \mathrm{TL/TA} - 1.936 \times \mathrm{CACH/CL}})$$

Where, P is the probability of fraud in financial statements (from 0 to 1). When $P > 50\%$, financial statements are fraudulent; when $P < 50\%$, financial statements are non-fraudulent;
INV/TA – Inventories / Total assets; SAL/FA – Sales / Fixed assets; TL/TA – Total liabilities / Total assets; CACH/CL–- Cash / Current liabilities.

Conclusions

In research papers, financial ratios are analysed in order to determine the most fraud-sensitive ratios of financial statements with regard to company managers' and employees' motivation to commit fraud. It was found out that in most cases fraud is committed to show that the company keeps growing and to fulfil obligational conditions. Literary sources offer a wide range of such ratios. Theoretical analysis showed that profitability, liquidity, activity and structure ratios are analysed most often.

51 financial ratios were investigated during the empirical research. Financial ratios, the values of which could indicate about fraud in financial statements were distinguished. A logistic regression model was developed to predict fraud in financial statements on the basis of financial ratios. The designed model can be used by external users of financial statement information when making decisions for investment and company evaluation.

References

Beneish, M. D. (1999). The detection of earnings manipulation. *Financial Analysts Journal*, *55,* 24–36.

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

Fanning, K. M., & Cogger, K. O. (1998). Neural network detection of management fraud using published financial data. *Intelligent Systems in Accounting, Finance & Management, 7,* 21–41.

Feroz, E. H., Kwon, T. M., Pastena, V. S., & Park, K. (2000). The efficacy of red flags in predicting the SEC's targets: an artificial neural networks approach. *Intelligent Systems in Accounting, Finance & Management*, *9,* 145–157.

Gaganis, C. (2009). Classification techniques for the identification of falsified financial statements: a comparative analysis. *Intelligent Systems in Accounting, Finance & Management*, *16,* 207–229.

Kaminski, K. A., Wetzel, T. S., & Guan, L. (2004). Can financial ratios detect fraudulent financial reporting? *Managerial Auditing Journal*, *1,* 15–28.

Kirkos, E., Spathis, Ch., & Manolopoulos, Y. (2007). Data mining techniques for the detection of fraudulent financial statements. *Expert Systems with Applications*, *32,* 995–1003.

Lenard, M. J., & Alam, P. (2009). An historical perspective on fraud detection: from bankruptcy models to most effective indicators of fraud in recent incidents. *Journal of Forensic & Investigative Accounting*, *1,* 1–27.

Perols, J. (2011), Financial Statement Fraud Detection: An Analysis of Statistical and Machine Learning Algorithms. *Auditing: A Journal of Practice & Theory*, 30, 19–50.

Persons, O. (1995). Using financial statement data to identify factors associated with fraudulent financing reporting. *Journal of Applied Business Research, 11,* 38–46.

Pustylnick, I. (2009). *Combined algorithm for detection of manipulation in financial statements*. SMC University, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1422693.

Pustylnick, I. (2012). An algorithm for the detection of revenue and retained earnings manipulation. *Accounting and taxation, 4,* 95–105.

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

Song X. P., Hu Z. H., Du J. G., & Sheng Z. H. (2014). Application of Machine Learning Methods to Risk Assessment of Financial Statement Fraud: Evidence from China. *Journal of Forecasting*, *33*, 611–626.

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

Stice, J. D. (1991). Using Financial and Market Information to Identify Pre-Engagement Factors Associated with Lawsuits against Auditors. *The Accounting Review, 66,* 516-533.

Wells, J. T. (1997). *Occupational fraud and abuse*. Austin, TX: Obsidian Publishing.