RAKSTI

EKONOMIKA

Julija Liodorova, Irina Voronova

FINANCIAL RATIOS FOR DETECTION OF COMPANY'S INSOLVENCY AND BANKRUPTCY FRAUD: SIMILARITIES AND DIFFERENCES

DOI: https://doi.org/10.9770/szv.2020.1(1)

This research is aimed to identify the similarities and differences of financial ratios used in the international methods for detecting insolvency (bankruptcy) and bankruptcy fraud. This is the first step in the process of developing a Latvia model of bankruptcy fraud detection. The methods of research: literature review, analysis and synthesis, comparative and correlation analysis. The selection of the analysed financial ratios is based on data from 28 bankruptcy forecasting models tested in Latvia and Lithuania, developed on the basis of multiple discriminant and regression analysis. In addition, the ratios of 3 analogical models for detecting fraud are also analysed. 58 indicators for bankruptcy forecasting were included in the study, selecting 19 indicators, which are also used to reveal fraud in financial statements (FFS) and to detect bankruptcy fraud in experts' and auditors' practice. The forensic methods to detect bankruptcy fraud, the international guidelines to reveal FFS, legislative acts and scientific research in this area are reviewed with the purpose to identify and analyse the similarities and differences in detecting insolvency (bankruptcy) and bankruptcy fraud. This type of complex analysis has not been presented in the Baltic countries yet. The article presents the testing results of fraud's revealing score models (M-score, F-score) using a sample of data obtained manually from financial statements of 114 small and medium companies in Latvia. It has been concluded that it is necessary to implement the system of financial ratios and assess the possibility to use fraud's revealing models in accounting examination. The authors stated the impossibility of using the M-score and F-score models without calibration for Latvia companies. The logistic regression model for revealing fraud (Lithuania) one year before the fact of bankruptcy forecasts the possibility of the bankruptcy fraud with an accuracy of 61.5%. The results of the study can be used both to create a model for detecting bankruptcy fraud and to develop an accounting expertise procedure to reveal fraud.

Key words: insolvency, bankruptcy fraud, financial ratio, model, financial statement, Latvia.

Finanšu rādītāji uzņēmuma maksātnespējas un krāpnieciska bankrota noteikšanai: līdzības un atšķirības

Šī pētījuma mērķis ir salīdzināt finanšu rādītāju līdzības un atšķirības, ko izmanto starptautiskajās metodēs maksātnespējas (bankrota) un krāpnieciska bankrota noteikšanai. Tas ir pirmais solis krāpnieciska bankrota noteikšanas Latvijas modeļa izstrādes procesā. Pētījuma metodes: literatūras apskats, analīze un sintēze, salīdzinošā un korelācijas analīze. Analizēto finanšu rādītāju izvēle balstās uz koeficientiem, kas iekļauti 28 maksātnespējas (bankrota) prognozēšanas modeļos, kas izstrādāti uz daudzdimensiju diskriminantas un regresijas analīzes pamata un ir pārbaudīti Latvijā un Lietuvā. Papildus tam tika analizēti finanšu rādītāji no 3 finanšu krāpšanas atklāšanas analoģiska tipa modeļiem. Kopumā pētījumā tika iekļauti 58 rādītāji bankrota prognozēšanai, no kuriem tika atlasīti 19, kas vienlaicīgi izmantoti ekspertu un auditoru praksē krāpšanas atklāšanas finanšu pārskatos (KFP) un krāpnieciska bankrota noteikšanai. Maksātnespējas (bankrota) un krāpnieciska bankrota noteikšanas līdzību un atšķirību identificēšanai un analīzei tika apkopoti ar šo jomu saistītie normatīvie akti un zinātniskie pētījumi, kriminālistikas metodes krāpnieciska bankrota noteikšanai un starptautiskās vadlīnijas KFP atklāšanai. Rakstā prezentēti krāpšanas atklāšanas skoringa modeļu *(M-score, F-score)* testa rezultāti, balstoties uz manuāli iegūtiem finanšu pārskatu datiem par 114 Latvijas mazajiem un vidējiem uzņēmumiem. Līdz šim brīdim finanšu krāpšanas atklāšanas modeļu visaptverošā analīze un modeļu piemērojamības pārbaude Baltijas valstīs nebija veikta. Pētījuma rezultātā tiek secināts, ka ir nepieciešams pārskatīt grāmatvedības ekspertīzē izmantoto finanšu rādītāju sistēmu krāpnieciska bankrota noteikšanai,un sniegti priekšlikumi tās pilnveidošanai. Autores ierosina izvērtēt iespēju krāpšanas atklāšanas modeļus izmantot grāmatvedības ekspertīzē, tomēr konstatēja, ka bez kalibrēšanas *M-score* un *F-score* modeļi nav piemēroti Latvijas uzņēmumiem. Krāpšanas atklāšanas loģistiskās regresijas modelis (Lietuva) gadu pirms bankrota iestāšanās prognozē krāpnieciska bankrota iespējamību ar precizitāti 61.5%. Pētījuma rezultāti varētu tikt izmantoti gan krāpnieciska bankrota noteikšanas modeļa izveidei, gan grāmatvedības ekspertīzes procedūras izstrādei krāpšanas atklāšanai.

Atslēgas vārdi: maksātnespēja, krāpniecisks bankrots, finanšu koeficients, modelis, finanšu pārskats, Latvija.

Финансовые показатели для обнаружения неплатёжеспособности и мошеннического банкротства предприятия: сходства и различия

В данном исследовании проводится сравнение финансовых коэффициентов, используемых в международных методах обнаружения неплатёжеспособности (банкротства) и мошеннического банкротства с целью идентификации сходств и различий в их использовании. Это – первый шаг на пути к разработке латвийской модели для обнаружения мошеннического банкротства. Методы исследования: обзор литературы, анализ и синтез, сравнительный и корреляционный анализ. Выбор анализируемых финансовых коэффициентов основан на показателях, включённых в 28 моделей прогнозирования банкротства на основе многомерного дискриминантного и регрессионного анализа, протестированных в Латвии и Литве. Также проанализированы коэффициенты 3 моделей выявления финансового мошенничества аналогичного типа. В исследовании было включено 58 коэффициентов прогнозирования банкротства, среди которых отобраны 19 индикаторов, используемых также экспертами и аудиторами для выявления мошенничества в финансовой отчётности (МФО) и обнаружения мошеннического банкротства. Для идентификации и анализа сходств и различий в обнаружении неплатёжеспособности и мошеннического банкротства в статье обобщены законодательные акты и научные исследования в данной области, методы судебной экспертизы по обнаружению мошеннического банкротства и международные руководства по выявлению МФО. В статье представлены результаты тестирования скоринговых моделей выявления мошенничества *(M-score, F-score)* на основе данных, полученных вручную из финансовых отчётов 114 латвийских малых и средних предприятий. Такого рода комплексный анализ и тестирование моделей выявления финансового мошенничества в странах Балтии проведён впервые. Авторы пришли к выводу о необходимости пересмотра системы финансовых коэффициентов для обнаружения мошеннического банкротства, используемой в бухгалтерской экспертизе, и внесли предложения по её улучшению. Авторы предлагают также рассмотреть возможность использования в бухгалтерской экспертизе моделей выявления мошенничества, однако констатировали невозможность использования моделей *M-score* и *F-score* без калибровки для латвийских предприятий. Модель логистической регрессии выявления мошенничества (Литва) за год до наступления факта банкротства предсказывает возможность мошеннического банкротства с точностью 61.5%. Результаты исследования могут быть использованы как при создании модели обнаружения мошеннического банкротства, так и для разработки процедуры бухгалтерской экспертизы по выявлению мошенничества.

Ключевые слова: неплатежеспособность, мошенническое банкротство, финансовый коэффициент, модель, финансовая отчетность, Латвия.

Introduction

The topicality of fraud within the cases of insolvency (bankruptcy)[1] has been substantiated by Deloitte report drawn up according to the order of the Foreign Investors' Council in Latvia (FICIL). According to the report, during the period of 2008–2014, financial cost of insolvency in Latvia accounted for 6.6 billion EUR or 27% if compared to Latvia's GDP in 2014. Insolvency abuse amounted to 74.3% and 76.8% of the cases related to fraud in financial statements (Deloitte 2016).

According to the report of the Association of Certified Fraud Examiners (ACFE), out of the three major categories of occupational fraud the losses caused by fraud in financial statement are the largest ones, accounting for 975 000 USD (ACFE 2016). The Financial Intelligence Unit (FIU) of Latvia recognises bankruptcy fraud as one of the main domestic money laundering risks (FIU 2018).

There are two conceptual approaches to identifying bankruptcy fraud. The international guidelines have the general indications of "red flags" for fraud detection in financial statementsin the countries based on the Anglo-Saxon law system. The financial and non-financial indicators for detecting bankruptcy fraud are specified in the national laws and regulations in countries based on the Romano-Germanic law system.

Assessment of the development rating of bankruptcydetection for the Baltic countries is provided in B. Prusak study: Estonia – 3, Latvia – 2, Lithuania – 2.5 (according to a 4-point scale) (Prusak 2018). The literature review on bankruptcy detection and the verified models in Latvia and Lithuania identified 28 bankruptcy forecasting models. There are many studies on the causes of various risks of bankruptcy in Estonia.

At least two models have been developed to reveal fraud in financial statements:

[1] The term "insolvency" or "bankruptcy" is used differently in national laws. The term "bankruptcy" is commonly used in bankruptcy cases related to fraud and is most often described as a "bankruptcy fraud".

M-score model (Beneish 1999) and its modification – F-score (Dechow et al. 2011) model. Recent scientific publications have revealed a tendency to combine bankruptcy forecasting and fraud identificationin financial statements using M-score model (Wadhwa et al. 2020).

In Latvia and Lithuania, for the detection of bankruptcy fraud forensic experts use only financial ratios, while Estonia experts also use the Altman models. The authors have not found any studies about Mscore model in the Baltic countries.

The aim of the study is to identify similarities and differences between financial ratios used in identifying insolvency (bankruptcy) and bankruptcy fraud for their subsequent possible use to build model for detecting bankruptcy fraud.

To achieve the goal, the first objective of the research is to determine the financial ratios of bankruptcy fraud, using the legislation, bankruptcy and fraud detection models and experts' experience. The second objective is to test empirically the models for detecting fraud in financial statements for the bankrupt companies in Latvia caused by fraud.

The article describes the determination of financial ratios using the classic bankruptcy forecasting models, legislative acts, and guidelines for auditing, as well as show the results of their comparison. Empirical results of models for revealing fraud in financial statements (M-score, F-score and the logistic regression model for detecting fraud (Lithuania)) use in Latvia are describedalso.

This article presents the first stage of the complex entire study of the authors.

Literature review

Detection and proof of bankruptcy fraud have become possible with the introduction of mandatory financial statements and tightening of the rules for drawing up the statements. The financial ratios can be used to reveal fraud; they are also useful at all stages of an audit or an accounting examination, from planning to final assessment (Guan et al. 2004).

The main achievement in the fight against bankruptcy fraud was creating a methodology for assessing bankruptcy and its timely forecasting. The first step was to determine the insolvency (bankruptcy) ratios, such as liquidity, solvency, profitability and activity. The next step was to create a different type of forecasting models, for example, the risk index scores, multiple discriminant analysis (MDA), the models with conditional probability as logit/probit type and others.

The authors' previous literature review about bankruptcy diagnostics in the period from 1998 to 2017 in Latvia (Liodorova, Voronova 2018a) demonstrated that 19 foreign bankruptcy forecasting models were tested based on the financial statements of Latvia companies; four Latvia models had been created since 1998. The authors added the Olhson model recommended for assessing solvency in auditing (Sneidere 2007), but it was not tested in Latvia; the Poland Credibility Index model was verified as Tamari model in Latvia (Skiltere, Zuka 2006). The authors determined the ratios of Tamari model (Ivanickova et al. 2016), quantitative indicators of Argenti score, and added the Skiltere/Zuka scoring model (Skiltere, Zuka 2010). The Depalan's model (Sneidere 2007) was not found in other studies.

In addition, the accuracy of the Chesser (1974), Slovak's (1995–2005) and Zavgren (1983) models has been examined in Lithuania (Kanapeckiene, Marcinkevicius 2014). The regional bankruptcy forecasting logit/probit model has been developed in Lithuania (Grigaravicius 2003); the economists have looked for the differences between financially sustainable and insolvent companies (Stoskus et al. 2007). The model included in the list (see Appendix 1) has been examined for practical use in forecasting bankruptcy of Latvia companies.

There are many studies on the causes of bankruptcy, including attempts by managers to hide information in financial statementsin Estonia (Lukason, Camacho-Minano 2019).

Despite the rapid development of insolvency (bankruptcy) forecasting in the world without any differences, there are differences in establishing evidence of bankruptcy fraud in countries based on the Romano-Germanic and Anglo-Saxon law systems.[2]

Thus, the detection of bankruptcy fraud in countries based on the Romano-Germanic law system, such as the Baltic countries, Russia, Belarus, Ukraine and others, consists of two stages: the determination of economic insolvency and identification of the fraudulent or anomaly transactions, which lead to the company's bankruptcy results. Determination of insolvency and fraud risk is based on the analysis of financial statements, using the financial ratios. The identification of fraudulent transactions is based on the detailed analysis of financial documentation (bank statements, accounting ledgers, contracts, etc.). This documentation is available only to investigators and auditors.

Baltic legislation mentions only non-financial indicators for detecting bankruptcy fraud: transactions with stakeholders, indemnity transactions, etc.; financial ratios are not considered. Detection methodology is not open information to public use in the Baltic countries. The forensic accountants use a complex approach to the financial analysis. Courts do not apply the developed and verified bankruptcy forecasting models in practice (Spieciute et al. 2013). The financial and non-financial indicators for detecting bankruptcy fraud are specified in legal acts of the Russian Federation, the Republic of Belarus, Ukraine (Liodorova et al. 2019), but there is no information about the application of any bankruptcy forecasting model to establish evidence of bankruptcy fraud in these countries.

Detection of fraud, including bankruptcy fraud in countries based on the Anglo-Saxon law system, such as the USA, Canada, Great Britain, Australia and others, implies the auditing of the financial statements, using various analysis methods. There are guidelines for detecting fraud in financial statements intended for auditors and fraud examiners. For example, Standard No 99 of Statement of Auditing Standards – SAS (AICPA 2002) developed by the American Institute of Certified Public Accountants (AICPA) describes the general auditing methods forthe detection and prediction of

---

[2] The definition of bankruptcy fraud is given and its forms are described in the previous study of the authors (Liodorova, Voronova 2018b).

fraud (AICPA 2002). The guidelines (Golden et al. 2006) for fraud detection are recommended by ACFE, and they have general indications of "red flags" – the financial and non-financial fraud predictors. Guidelines also contain recommendations for the financial ratios, which should be analysed to detect bankruptcy fraud.

To reduce the subjectivity of selection of financial ratios for assessing bankruptcy and/or fraud risk, associations of specialists engaged in the examination and analysis of finances constantly work on improving their methods, including new scientific achievements. The National Association of Certified Valuators and Analysts (NACVA) published the review of scientific studies of fraud detection models (Bishop et al. 2017).

To assess the intentional falsification of financial statements and the likelihood of fraudulent reporting, the mathematical models have been developed. M-score manipulation index developed by M. Beneish (Beneish 1999) is a mathematical model, which consists of eight financial ratios to identify earnings manipulation. M. Beneish's research has shown that the value of the M-score composite index for organisations that manipulate their earnings exceeds 2.22. Three various F-score models were developed by P. Dechow and his colleagues (Dechow et al. 2011), which differed in terms of the ratios used, related to information availability. Research has shown that the value of the F-score index for companies' fraudulent statements – for example, in the case of Enron, – exceeds 2.45.

After this period, the authors can highlight the research by C. Corsi and his colleagues (2015) as well as by H. A. Nguyen and H. L. Nguyen (2016). The research conducted by H. A. Nguyen and H. L. Nguyen (2016) provides an overview of most important previous studies on the use of M-score performed in the USA, Italy, India, Malaysia, the UK and Nigeria in the period of 2011–2014.

All studies have been performed on the basis of joint stock companies whose reports are publicly available. The sample of the investigated fraud cases is small. The results of some studies about bankruptcy and fraud in financial statements are presented in Table 1.

Table 1

Studies on the ability of financial ratios to detect fraud in financial statements – FFS

Author, year	Object of the study	Purpose of the study	Main results of financial ratios
Pearsons O. (1995)	103 fraudulent and non-fraudulent companies on the basis of industry and period Period: 1970–1990	Examining variables to evaluate FFS models and assessing their predictive ability using logistic regression	Capital turnover, financial leverage and asset composition are significant factors associated with FFS
Spathis C. (2002)	76 manufacturing companies: 38 companies with FFS and 38 – without FFS Period: 2000	Development of a financial ratio model to detect FFS using logistic regression	Companies with high inventory and debts, low profitability, and Z-score are more likely to use FFS Receivables show the ability to manipulate with earnings
Kaminski K. et al. (2004)	158 companies: 79 companies with FFS and 79 – without FFS Period: 1982–1999	Examining whether financial ratios of fraudulent companies differ from the ratios of health companies	Five ratios are significant during the period prior to the fraud year The limited ability of ratios to detect FFS
Lenard M. et al. (2009)	73 companies in the computer technology services industry: 30 companies that were subject to litigation and 43 healthy companies Period: 1996–2004	Studying the development of FFS models over the years and determining their relative usefulness. (descriptive statistics, Persons', Altman's, Lenard's models, etc.)	Models that detect bankruptcy can also indicate fraud Combination of accounting rules, regulation, and government enforcement helps develop FFS
Dalnial H. et al. (2014)	130 companies: 65 fraudulent and 65 non-fraudulent Period: 2000–2011	Identifying which financial ratios are significant to fraudulent reporting	Total debt to asset, receivables to revenue, Z-score are significant predictors to detect FFS Ratios may be helpful to detect FFS
Nia S. (2015)	134 companies Period: 2009–2014	Investigating differences between the mean of financial ratios of fraud and non-fraud companies	Difference between the ratios of current assets, inventory and revenue to total assets is significant
Ragab Y. (2017)	66 companies Period: 2009–2015	Identifying significant financial ratios to FFS; developing a logistic regression model to detect fraud	Three variables: asset turnover, operating profitability and financial leverage were entered in the model

Source: compiled by the authors.

The studies do not reveal any differences between the adjusted version of M-scoreIt (Italia) and the simplified model for European companies (Corsi et al. 2015). Results of the research realized by H. A. Nguyen and H. L. Nguyen (2016) indicate that the M-score model may be considered suitable for selective observations in Vietnam, as the results of research are also consistent with the audit reports on information disclosure in 2014. According to Y. Egorushkina *(Ю. Егорушкина)* (2017), the use of models developed on the basis of the information of foreign countries is not possible because the features and characteristics of the Russian economy are not taken into account. The application of M-score and F-score has revealed significantly different results: the degree of mismatch – 47.04%, the coincidence of the results on the manipulation – 18.64%, non-manipulation – 34.32%.

The model of fraud detection has been developed in Lithuania (Kanapickiene, Grundiene 2015). The authors of the present study have not found any research on the use of M-score and F-score conducted in Estonia, Latvia and Lithuania.

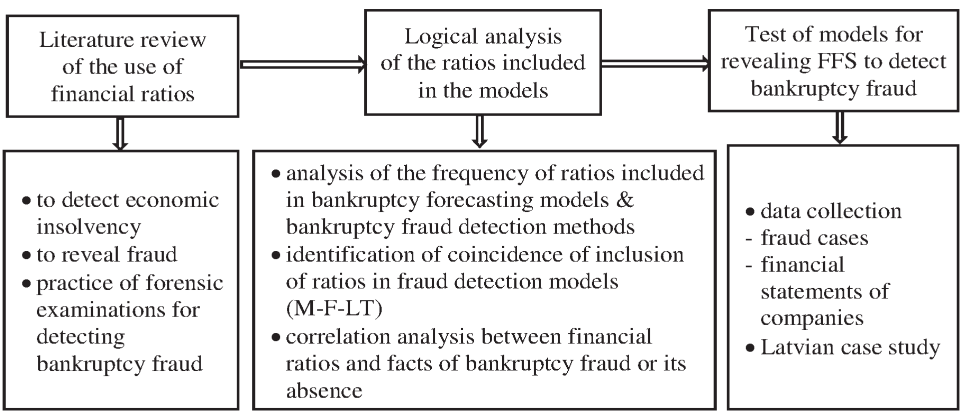
Experts and scientists discuss the effectiveness of using financial ratios to reveal fraud in financial statements (FFS). However, there is no consensus on this issue: some studies show that financial ratios may be helpful to detect FFS; other studies prove the limited ability of financial ratios to detect FFS.

Methodology of the study

The authors' complex research methodology – the development of a bankruptcy fraud detection model for use in forensic examination consists of several stages: literature review of the use of financial ratios for detecting bankruptcy and fraud, logical analysis of the ratios included in the models, correlation analysis between financial ratios and facts of bankruptcy fraud, and test of models for revealing fraud in financial statements (FFS) to detect bankruptcy fraud (see Figure 1).

Figure 1

Process of developing a model for detecting bankruptcy fraud



Source: compiled by the authors.

Comparison of forensic approach to detecting insolvency (bankruptcy) and bankruptcy fraud

The authors' previous study (Liodorova, Voronova 2018a) regarding the models tested in Latvia and Lithuania presents 28 models. International forecasting models, such as the Altman, Liss, Zmijewski, Fulmer, etc., and regional models, such as Sorin/ Voronova (Latvia), Grigaravicius (Lithuania), etc. have been included in the list.

There are 58 ratios, which are included in all models 142 times. The most commonly used ratios are the profitability ratio – 16, solvency ratio – 11, activity ratio – 10, liquidity ratio – 9 and others, which cannot be clearly attributed to a particular group – 12, such as the development of the net profit-to-profit ratio included in Tamari and Ohlson models, total assets-to-GNP price-level index in Ohlson model (Sneidere 2007; Ivanickova et al. 2016).

The determined ratios and their number are represented in Table 2. Items from the financial statements used for ratio accounting are presented in Appendix 2.

Table 2

The most commonly used financial ratios in bankruptcy forecasting models

Type	Ratio	Inclusion frequency in bankruptcy forecasting models (times)			Type	Ratio	Inclusion frequency in bankruptcy forecasting models (times)		
		Foreign models	LV, LT	Total			Foreign models	LV, LT	Total
Profitability	S/TA	9	4	35	Solvency	E/TL	8	3	26
	EBIT/TA	8	3			TL/TA	5	3	
	NP/TA	8	3			E/TA	4	3	
Liquidity	CA/CL	5	2	7	Others	EBIT/ %	3	3	6
Activity	WC/TA	7	2	9		Total	57	26	83

Source: compiled by the authors.

As a result, nine of the most commonly used bankruptcy financial ratios have been selected which are included in models 83 times (see Table 2). Such ratios are profitability – 3 ratios disclosed in 11–13 models, solvency – 3 ratios (7–11 models), activity – 1 ratio (9 models), liquidity – 1 ratio (7 models), other – 1. The authors note, there are also inverse ratios used in some models, but it does not change the ratio's gist.

The study has shown that the most popular ratios used for bankruptcy prediction 100% are included in nine models: all Altman's models, Sorin/Voronova (Latvia) model, Liss and Zmijewski models, Savicka risk index scoring model and Slovakia IN05 model. None of the selected ratios are included in two models – Zavgren and Chesser models.

An analysis of forensic practice to identify insolvency (bankruptcy) has shown that countries based on the Romano-Germanic legal system,[3] including the Baltic countries, use a normative approach comparing the calculated financial ratios with its normative value (Liodorova et al. 2019). The legislative acts establish 10 obligatory ratios that are used in forensic examination to detect bankruptcy fraud in the Russian Federation, the Republic of Belarus and Ukraine. Only two common ratios – solvency and liquidity ratios – are identified in all countries' laws, which areused for the detection of bankruptcy fraud in Latvia. The obligatory of profitability are used only in Latvia and Ukraine; the ratios of company's activity – and in Belarus. The liquidity ratios are used in Latvia, Russia and Ukraine.

Table 3 presents the identified financial ratios to detect bankruptcy fraud using forensic methods based on the Romano-Germanic law system and the application of these ratios to detect economic insolvency.

Table 3

Financial ratios for detecting bankruptcy fraud used by forensic methods based on the Romano-Germanic law and their application for insolvency detection

Type	Ratio	Countries that use it				Included in bankruptcy forecasting models (times)		
		LV	UA	RU	BY	Foreign	LV, LT	Total
Profitability	NP/E	√				2	–	2
	S/Cost		√			–	–	
Solvency	E/TL	√				8	3	19
	TL/TA	√	√	√	√	5	3	
Liquidity	CA/CL	√	√	√	√	5	2	13
	Cash/CL	√	√	√		2	1	
	CA/TL		√			2	1	
Activity	WC/TL	√	√			1	–	3
	WC/CA				√	1	1	
	CL/(S/t)			√		–	–	
Total						26	11	37

Source: compiled by the authors.

Nine out of ten financial ratios used to detect bankruptcy fraud by forensic accountants in countries with the Romano-Germanic law system are included 37 times in the Bankruptcy forecasting models (see Table 3). Such ratios are solvency – 2 ratios, liquidity – 3 ratios, activity – 3 ratios and profitability – 2 ratios. There are not exact financial ratios for insolvency or bankruptcy fraud detection in the countries' legislation

[3] Judicial decision is based on the common law system that is the legal tradition in the country. The Romano-Germanic law system is based on principles (legislative acts), the Anglo-Saxon law system is based on precedents summarizing practical examples.

based on the Anglo-Saxon law system, such as USA, UK, Australia etc. Instead, there are the publicly available international standards and guidelines for auditors and forensic accountants, who inspect the financial statements; the method choice is the personal issue. There are nine main ratios recommended for detecting fraud in financial statements (FFS) (Corbett, Clayton 2006). Some of them are used in countries with the Romano-Germanic law and are included in the insolvency forecasting models (see Table 4).

Table 4

Financial ratiosofFFS recommended for auditors and their use to detect bankruptcy fraud and insolvency (bankruptcy) in countries based on the Anglo-Saxon law

Type	Ratio	Countries that use it				Included in bankruptcy forecasting models (times)		
		LV	UA	RU	BY	Foreign	LV, LT	Total
Profitability	NP/S					–	2	15
	S/TA					9	4	
Solvency	TL/E	√				8	3	11
Liquidity	CA/CL	√	√	√	√	5	2	10
	Cash/CL	√	√	√		2	1	
Activity	Cost/Inv in days					2	–	4
	S/Rec in days					2	–	
Total						28	12	40

Source: compiled by the authors.

The SAS 99 (AICPA 2002) recommends considering unusual or unexpected relationships for fraud detection. Fraud predictors are the changes in inventory, liabilities, sales or cost of sales. Auditors' task is the evaluation of fraud risk and its likelihood, which is mainly related to revenue recognition, inventory quantities and management estimates.

According to the International Standard on Auditing (ISA) 570 indication, "adverse key financial ratios" may include the general financial ratios. The main aims of fraud in financial statements are revenue recognition and misappropriation of assets (Golden et al. 2006). One of the schemes of financial misstatements is the intent of company's value overstating (Frank et al. 2006). It is characterised with direct relationship between overstatement of assets and understatement of liabilities and expenses, which is used in scandals related to world corporative bankruptcy.

There are some differences in the use of financial ratios to detect financial fraud depending on the legal system of countries. However, despite the difference in legislation, all specialists pay special attention to the quick liquidity ratio (see Tables 3 and 4). It means that availability of cash plays an important role in assessing financial fraud.

According to international accounting standards for annual reports and legislation, a cash flow statement is not required for small companies, so it cannot be available in all investigations. Thereby, the analysis of this statement is not popular in countries based on the Romano-Germanic law system; however, the study of bank statements and the identification of cash use are the most important procedures in economic examination.

The profitability and cash flow are the main solvency indicators of "going concern" company, according to the ISA 570 (IFAC 2009), adopted only for auditing of financial statements, which do not contain mistakes and fraud. The negative operating cash flow and substantial operating losses are separate insolvency (bankruptcy) predictors. According to the SAS 99 (AICPA 2002), predictors of company's bankruptcy in fraudulent financial statements are the anomaly changes in profitability and ability to generate a cash flow. One of the recommended ratios is the relationship of net income to operating cash flow. Thus, a cash flow analysis should be used to evaluate bankruptcy fraud.

Only four of the described bankruptcy forecasting models contain ratios that include cash flow; two models contain ratios of commensurability of profitability with the availability of cash (see Table 5).

Table 5

Financial ratios of cash availability and their use to predict insolvency

Commensurability of profitability with availability of cash		**Payment ability**	
Ratio	Model that contains it	Ratio	Model that contains it
NP / Operating cash flow	–	Cash flow / TL	Fulmer Poland Credibility index Skiltere/Zuka MDA
Cash flow / S	Kralicek		
S / Cash	Chesser		
Cash / Profit	Zavgren	(TL – Cash) / Cash flow	Kralicek
Total inclusion frequency			7

Source: compiled by the authors.

To predict or detect bankruptcy fraud, the auditors and forensic accountants should also analyse other indicators: the relationship between a company's profitability to industry trends, changes in sales volume to personal statistic, etc. They must determine all "red flags" that are the changes in asset estimates, changes in the earning trends and incomes, and must examine the cash flow in bank statements and other non-financial information.

The authors have analysed the ratios included in the three fraud identification models, which are described in the next Chapter: M. Beneish M-score to identify manipulations with reported earnings, F-score by P. Dechow and his colleagues (2011) and Lithuania model (LT) by R. Kanapeckiene and Z. Grundiene (2015) to detect fraud in financial statements (FFS). The financial ratios of fraud detection models that are simultaneously used to detect fraud and bankruptcy were identified (see Table 6).

Table 6

Financial ratios of fraud identification models and their use to detect FFS, bankruptcy fraud, and insolvency (bankruptcy)

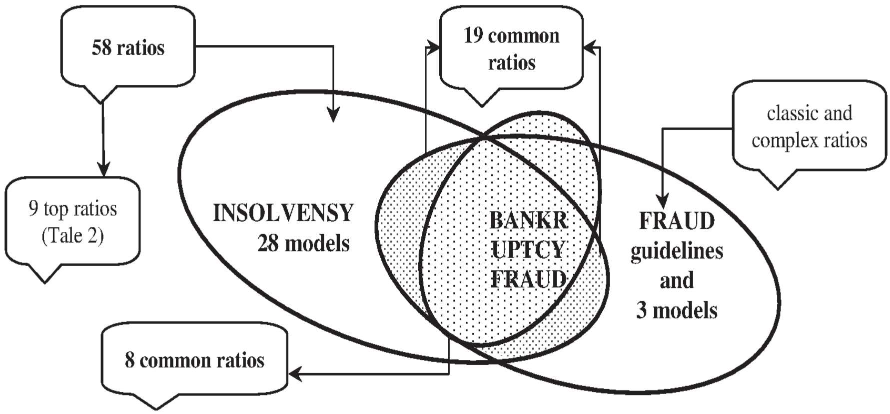
Type	Ratio	Fraud detection model			Used for fraud detection		Included in the bankruptcy forecasting models		
		M-score	F-score	LT-model	Bankruptcy tey fraud	FFS	Foreign	LV, LT	Total
Profitability	EBIT/TA		√				8	3	11
Solvency	TL/TA	√		√	√		5	3	8
Liquidity	Cash/CL			√	√	√	2	1	3
Activity	S/Rec	√	√			√	2	–	2
	Inv/TA		√	√			1	–	1
						Total	18	7	25

Source: compiled by the authors.

All types of financial ratios are used in fraud detection models. The Lithuania model contains three ratios that are used for bankruptcy forecasting, and crosses both fraud detection models (M-score, F-score). F-score model contains three ratios used for; M-score – two ratios. Three ratios included in models for revealing fraud in financial are used for fraud detection, including bankruptcy fraud (see Table 6). The feature of F-score and M-score fraud detection models is the inclusion of the changes in financial ratios compared with the previous period. Summarising the comparison results, similarities and differences have been identified. All types of financial ratios are used for detection of company's insolvency (bankruptcy) and bankruptcy fraud: profitability and solvency ratios are more often used to bankruptcy forecasting; liquidity ratios are more often used to detect fraud. Out of 58 analysed bankruptcy forecasting ratios, a total of 19 ratios were identified that are used to detect fraud in financial statements, including bankruptcy fraud. Currently, only 8 ratios are used to detect bankruptcy fraud in the expert practice (see Figure 2).

Figure 2

Financial ratios used to detect bankruptcy fraud and insolvency (bankruptcy)



Source: compiled by the authors.

The authors have conducted a study on the use of more important financial ratios applied to detect fraud. These ratios are included in insolvency forecasting models to detect bankruptcy fraud using a pairwise correlation between the fact of bankruptcy fraud and financial ratios. The analysed ratios were calculated a year before bankruptcy. In accordance with the importance of identifying anomalous changes in order to reveal fraud in financial statements, the authors have analysed changes in the values compared with previous year. The results of the conducted study are presented in Table 7.

Table 7

Correlation between financial indicators and fact of bankruptcy fraud or its absence

Correlation	Financial ratios								
	NP/S	S/TA	EBIT/TA	E/TL	TL/TA	CA/CL	WC/CA	Inv/TA	S/Rec
Fact of bankruptcy fraud and ratio (t_{-1} year)	-0.32	-0.24	-0.40	-0.19	0.40	-0.27	-0.29	-0.16	-0.17
Fact of bankruptcy fraud and change of ratio ($t_{-1} - t_{-2}$ year)	0.22	0.02	0.16	0.19	0.37	0.16	0.23	0.27	-0.18

Source: compiled by the authors.

The correlation above 0.1 has been found for nine financial ratios reviewed in the study, which confirms the results of other studies (see Appendix 1): capital turnover, financial leverage, asset composition, sale to receivables, etc. However, such a correlation does not allow using only certain financial ratios to detect bankruptcy fraud as forensic evidence.

Application of models for revealing fraud in financial statements to detect bankruptcy fraud: a case of Latvia

The methods of fraud detection based on "red flags" or financial ratios without the use of specified norms are related to subjective evaluation. In order to identify abnormal changes, the analysis must be carried out over time. According to such flaws, economic theory uses the statistic-mathematical methods.

One of the founders of the statistic-mathematical method for detecting fraud in financial statements was M. Beneish (1999), who developed the integral manipulation index M-score. There are two various M-score models that contain 5 and 8 variables (ratios). The commonly used model is the M-score with 8 ratios, the critical threshold of which is > -2.22 (Nguyen H. A., Nguyen H. L. 2016). According to M. Alekseev's *(М. Алексеев)* and M. Tiuzhina's *(М. Тюжина)* (2017) calculation, M-score for Russian companies was in the interval of -58.29 to 234.95. M-score formula is (1) (Nguyen H. A., Nguyen H. L. 2016):

$$M = -4.84 + 0.920 \cdot DSRI + 0.528 \cdot GMI + 0.404 \cdot AQI + 0.892 \cdot SGI + 0.115 \cdot DEPI - 0.172 \cdot SGAI + 4.679 \cdot TATA - 0.327 \cdot LVGI \quad (1)$$

The alternative method for fraud detection in financial statements is the F-score developed by P. Dechow and his colleagues (2011). There are three various F-score models, which contain 7 variables that are available from financial data; 9 variables that are used in non-financial indicators (change in employees, etc.); 11 variables, including the market-related indicators.

The F-score model with 7 financial variables is described in the present study. The F-score predicts the probability of fraud in the interval of 0–1. The authors of the model use the unconditional probability valued at 0.0037, based on their data (Dechow et al. 2011).

There are some obscurities in the variable determination in F-score model description. For example, there is the specific calculation of working capital for F-score model (Dechow et al. 2011); there is the difference between the calculation of accruals in the study by M. Alekseev and M. Tiuzhina (2017) and F-score by P. Dechow and his colleagues (2011).

F-score formula is (2) (Dechow et al. 2011):

$$F = -7.893 + 0.790 \cdot RSST_{ACC} + 2.518 \cdot Ch_{Rec} + 1.191 \cdot Ch_{Inv} + 1.979 \cdot \%_{Soft} + 0.17 \cdot Ch_{Cash} - 0.932 \cdot Ch_{ROA} + 1.029 \cdot Issue \quad (2)$$

Calculation of variables used in the present research is shown in Table 8.

Table8

Description of variables in M-score and F-score models

Ratio	Formula	Ratio	Formula
AQI	$\left[1-\frac{PPE_t+CA_t}{TA_t}\right]/\left[1-\frac{PPE_{t-1}+CA_{t-1}}{TA_{t-1}}\right]$	*DSRI*	$\left[\frac{Rec_t}{S_t}\right]/\left[\frac{Rec_{t-1}}{S_{t-1}}\right]$
DEPI	$\left[\frac{Amort_{t-1}}{Amort_{t-1}+PPE_{t-1}}\right]/\left[\frac{Amort_t}{Amort_t+PPE_t}\right]$	*LVGI*	$\left[\frac{TL_t}{TA_t}\right]/\left[\frac{TL_{t-1}}{TA_{t-1}}\right]$
SGAI	$\left[\frac{SGACost_t}{S_t}\right]/\left[\frac{SGACost_{t-1}}{S_{t-1}}\right]$	*GMI*	$\left[\frac{S_{t-1}-Cost_{t-1}}{S_{t-1}}\right]/\left[\frac{S_t-Cost_t}{S_t}\right]$
TATA	$\frac{(\Delta CA-\Delta Cash)-(\Delta CL-\Delta CPay)-Amort_t}{TA_t}$	*SGI*	$\frac{S_t}{S_{t-1}}$
Ch_{Rec}	$\Delta Rec/\overline{TA}$	Ch_{Inv}	$\Delta Inv/\overline{TA}$
$\%_{Soft}$	$Soft/TA$	Ch_{Cash}	$\Delta S/S-\Delta Rec$
Ch_{ROA}	$(EBIT_t/\overline{TA}_t)-(EBIT_{t-1}/\overline{TA}_{t-1})$	*Issue*	1 – if the firm issued securities during year t; 0 – if the firm did not issue securities
$RSST_{ACC}$	$\Delta WC^*+\Delta NCO+\Delta FIN/\overline{TA}$ $WC^*=(CA-Cash)-(CL-Debt\ in\ CL)$, $NCO=(TA-CA-Advances)-(TL-CL)$ $FIN=(StInvest+LtInvest)-(LtL+Debt\ in\ CL+Pr\ e\ ferreds\ stock)$		

Source: compiled by the authors based on Nguyen H. A., Nguyen H. L. 2016; Dechow et al. 2011.

The logistic regression model of fraud detection in financial statements, which was developed in Lithuania, is easier for calculation (Kanapeckiene, Grundiene 2015). More accurate model out of the three developed models contains four variables (ratios). The probability of fraud is in the interval of 0–1. The formula of the Lithuania fraud detection model is (3):

$$P=1/(1+e^{5.768-4.263\frac{Inv}{TA}-0.029\frac{S}{FA}-4.766\frac{TL}{TA}-1.963\frac{Cash}{CL}}) \quad (3)$$

The test of the feasibility of using fraud identification models to detect bankruptcy fraud in Latvia was conducted based on the financial statements of Latvia small and medium-sized companies. 54 of them went bankrupt due to recognized fraud and 60 companies free from fraud. The use of fraud models was verified on the basis of data one and two years prior to the bankruptcy.

The results of M-score application were obtained only for 34 companies for a year before bankruptcy (10 – two years before bankruptcy). It was not possible to obtain any results of M-score in other cases. This was due to the fact that reports did not contain deprecation information; sales were not recorded in some statements. Fraud was disclosed in 5 (6) financial statements of fraudulent bankrupts. On other hand, fraud was disclosed in 17 (1) reports of companies without recognized fraud. The range of M-score results was from -5.67 to 11.9 in cases of bankruptcy with fraud, from -9.76 to 43.9 in cases without revealed fraud. Thus, the M-score is not applicable to Latvia small and medium-sized companies or should be revised taken into account local conditions and legislation.

F-score showed a high probability of financial fraud in almost all statements including companies that are healthy from fraud. Results of F-score could not be accepted because F-score using unconditional probability was approximately 270 compared with a standard value of 2.45.

Fragment of the test results of the application of Lithuania model in Latvia are presented in Table 9 on the basis of data one year prior to the bankruptcy, In Table 9, the disclosed fraud is designated as "F", the absence of fraud – "NF", unused statements for counting – "no data", the company that went bankrupt due to recognized fraud is designated as "Fraud", the companies without revealed fraud – "Non-fraud", the company number is designated as "N" (see Table 9).

Table 9

Fragment of the test results of the application of the Lithuania model in Latvia

N	Fraud score, result	N	Non-fraud score, result	N	Fraud score, result	N	Non-fraud score, result	N	Fraud score, result	N	Non-fraud score, result
1	87%, F	1	43 %, NF	24	12%, NF	24	40%, NF	52	38%, NF	52	100%, F
2	11%, NF	2	100%, F	25	4%, NF	25	100%, F	53	3%, NF	53	80%, F
3	2%, NF	3	87 %, F	26	84%, F	26	7%, NF	54	1%, NF	54	5%, NF
4	48%, NF	4	23%,NF	27	100%, F	27	3%, NF	–	–	55	no data
5	41%, NF	5	no data	28	39%, NF	28	25%, NF	–	–	56	12%, NF
6	96%, F	6	14%, NF	29	19%, NF	29	8%, NF	–	–	57	68%, F
7	37%, NF	7	24%, NF	30	65%, F	30	18%, NF	–	–	58	12%, NF
8	69%, F	8	47%, NF	31	100%, F	31	12%, NF	–	–	59	100%, F
9	87%, F	9	100%, F	32	99%, F	32	48%, NF	–	–	60	43%, NF
20	no data	20	20%, NF	48	99%, F	48	20%, NF	F	30		20
21	100%, F	21	11%, NF	49	97%, F	49	98%, F	NF	22		37
22	no data	22	5%, NF	50	13%, NF	50	67%, F	no data	2		3
23	8%, NF	23	22%, NF	51	96%, F	51	100%, F	Total	54		60

Source: compiled by the authors.

Results of the Lithuania fraud detection model were obtained for 109 companies for a year before bankruptcy (110 – two years before bankruptcy) from the financial statements of 114 companies. The probability of fraud above 50% was disclosed in 30 (28) financial statements of fraudulent bankrupts; fraud was disclosed in 20 (24) reports of companies without recognized fraud (see Table 9). Thus, the overall accuracy of the Lithuania model using the two-error method was estimated at 61.5% (55.5%), where the type I error was 35.1% (42.1%) and the type II error was 42.3% (75.8%).

Conclusions

Literature review about the use of financial ratios to identify bankruptcy fraud in financial statements has distinguished three major problems: the differences in approaches to detecting bankruptcy fraud due to the peculiarities of traditional legal systems (based on the Romano-Germanic and Anglo-Saxon law systems); the insufficient basis for monitoring of fraud cases; the large number of indicators are regulated by legislative acts and guidelines.

The use of all types of financial analysis in the both law systems was established in this study: profitability, solvency, liquidity and activity.

The authors found that 19 common financial ratios are used for insolvency forecasting, detect fraud and bankruptcy fraud, which is 33% of all ratios analysed in the study. Pair correlation revealed a relationship between the 9 financial ratios and the fact of fraud a year before bankruptcy; 4 of them have a correlation -0.19–0.40 and are also included in the group of 8 ratios used to detect bankruptcy fraud: E/TL, CA/CL, WC/CA and TL/TA.

The substantial differences in the use of financial ratios to detect insolvency and bankruptcy fraud in countries based on the different law systems. The main ratios are liquidity and solvency ratios, which are used for bankruptcy fraud detection in countries based on the Romano-Germanic law. The main objects of manipulation in financial statements are income and earningsin countries based on the Anglo-Saxon law. Countries based on the Romano-Germanic law do not sufficiently use the ratios of profitability and activity; less attention is devoted to the analysis of cash flow statement compared with countries based on the Anglo-Saxon law.

The authors recommend updating the Latvia and Lithuania forensic methods for bankruptcy fraud detecting based on alternative ratios that are used internationally. For example, the activity ratios used for bankruptcy fraud detection should be reviewed and supplemented. It is necessary to supplement forensic methods for bankruptcy fraud detection with the analysis of cash flow, including some acceptable ratios. Consideration should be given to using ratios that capture changes over time, as in Tamari and Olhson models, or ratios included in the M-score and F-score models.

The authors tested three models for revealing fraud in financial statements based on the data of 114 Latvia small and medium-sized companies.

F-score and M-score models that are developed in countries based on the Anglo-Saxon law, are not applicable to Latvia companies or should be revised for local conditions; F-score has shown high probability of mistakes. The logistic regression model of fraud detection developed in Lithuania that is country based on the Romano-Germanic law, was more applicable for calculating the data of Latvia companies. The assessment of the possibility of manipulation using the Lithuania model was estimated at 61.5% a year before bankruptcy. The study has demonstrated that the portability of models developed in one country to another without reassessment of the coefficients instead of the original ones does not provide satisfactory results for their practical application in forensic examination.

The present research has also demonstrated that there are not only financial predictors of bankruptcy fraud. The results of the study have revealed a gap in the use of non-financial indicators of bankruptcy fraud detection. There is no cross-sectional approach between the indicators used in insolvency forecasting models and non-financial indicators of bankruptcy fraud. Therefore, a set of financial and non-financial indicators have to be used, applying the cross-approach to their relationship detection and valuation of influence. The areas of further research include a thorough study of the application of fraud detection models to one's own region and determination of the non-financial indicators of bankruptcy fraud.

References

ACFE (Association of Certified Fraud Examiners). (2016) *Report to the Nations on Occupational Fraud and Abuse: 2016 Global Fraud Study*. Available: http://www.acfe.com/rttn2016.aspx (accessed on 30.06.2020).

AICPA (American Institute of Certified Public Accountants). (2002) *Consideration of Fraud in a Financial Statement Audit, SAS99 in Statement of Auditing Standards*. Available: https://www.aicpa.org/Research/Standards/AuditAttest/ DownloadableDocuments/AU-00316.pdf (accessed on 30.06.2020).

Alekseev M. (2017) *Kontseptsiia informacionnogo prostranstva finansovogo rynka*. Dissertation. Novosibirsk: Novosibirsk State University of Economics and Management. (In Russian)

Alekseev M., Tiuzhina M. (2017) Proverka podkhodov k viiavleniiu napravleniia iskazheniia finansovoi otchetnosti. *Uchetno-analiticheskoe obespechenie biznesa,* № 3(122), s. 69–75. Available: http://journal.safbd.ru/ru/issues/2017-no3-122-may-iyun_article_69-75 (accessed on 30.06.2020). (In Russian)

Beneish M. (1999) The detection of earnings manipulation. *Financial Analysts Journal*, Vol. 55, No. 5, pp. 24–36. DOI: https://doi.org/10.2469/faj.v55.n5.2296

Bishop C., DeZoort F., Hermanson D. (2017) Review of recent literature on pressure on CFOs to manipulate financial reports. *Journal of Forensic & Investigative Accounting*, Vol. 9, No. 1, pp. 577–583. Available: http://web.nacva.com/JFIA/Issues/JFIA-2017-No1-1.pdf (accessed on 30.06.2020).

Corbett M., Clayton M. (2006) Analysing financial statements. Golden T., Skalak S., Clayton M. (Eds.). *A Guide of Forensic Accounting Investigation*. 2nd edition. New Jersey, NJ: John Willey & Song Inc, Chapter 19. Available: https://www.academia.edu/37544013/A_Guide_to_Forensic_Accounting_Investigation (accessed on 30.06.2020).

Corsi C., Berardino D., Cimbrini T. (2015) Beneish Mscore and detection of earnings management in Italian SMEs. *Ratio Mathematica*, Vol. 28, pp. 65–83. Available: http://www.eiris.it/ratio_numeri/ratio_28_2015/file_separati/6_n_28.pdf (accessed on 30.06.2020).

Dalnial H., Kamaluddin A., Sanusi A., Khairuddin K. (2014) Detecting fraudulent financial reporting through financial statement analysis. *Journal of Advanced Management Science*, Vol. 1, No. 1, pp. 17–22. DOI: https://doi.org/10.12720/joams.2.1.17-22

Dechow P., Ge W., Larson C., Sloan R. (2011) Predicting material accounting misstatements. *Contemporary Accounting Research*, Vol. 28, pp. 17–82. Available: https://doi.org/10.1111/j.1911-3846.2010.01041.x (accessed on 30.06.2020).

Deloitte. (2016) *Insolvency abuse report. Foreign Investors Council in Latvia*. Available: https://www.ficil.lv/wp-content/uploads/2017/04/16-04-06-FICIL-Insolvency-Abuse.pdf (accessed on 30.06.2020).

Egorushkina Y. (2017) Primenenie indeksov M-score i F-score dlia otchetnostei kompanii, zanimaiuschikhsia proizvodstvom produktov i napitkov. *Proceedings of the 21st International*

Scientific Conference "Sovremennaia ekonomika: aktual'nie voprosy, dostizheniia, innovacii", Chast' 4. Penza: MCNS "Nauka i Prosveschenie", s. 179–183. Available: https://naukaip.ru/wp-content/uploads/2018/01/%D0%9C%D0%9A-254-%D0%A7%D0%B0%D1%81%D1%82%D1%8C-4.pdf (accessed on 30.06.2020). (In Russian)

FIU (Financial Intelligence Unit). (2018) *Papildinats Latvijas Nacionalais NILLTF risku novertesanas zinojums*. Available: https://www.fid.gov.lv/images/Downloads/useful/NRA_LV_FINAL.pdf (accessed on 30.06.2020). (In Latvian)

Frank J., Jansen D., Ahmad J. (2006) Financial statement fraud: other schemes misappropriations. Golden T., Skalak S., Clayton M. (Eds.). *A Guide of Forensic Accounting Investigation*. 2nd edition. New Jersey, NJ: John Willey & Song Inc, Chapter 11. Available: https://www.academia.edu/37544013/A_Guide_to_Forensic_Accounting_Investigation (accessed on 30.06.2020).

Golden T., Skalak S., Clayton M. (Eds.). (2006) *A Guide of Forensic Accounting Investigation*. 2nd edition. New Jersey, NJ: John Willey & Song Inc. Available: https://www.academia.edu/37544013/A_Guide_to_Forensic_Accounting_Investigation (accessed on 30.06.2020).

Grigaravicius S. (2003) Corporate failure diagnosis: reliability and practice. *Management of Organizations: Systematic Research*, Vol. 28, pp. 29–42. Available: https://www.vdu.lt/cris/handle/20.500.12259/39089 (accessed on 30.06.2020).

Guan L., Kaminski K., Wetzel T. (2004) Ratio analysis – predictor of fraud? *Advanced in Public Interest Accounting,* Vol. 19, No. 1, pp. 17–34.

IFAC (International Federation of Accountants). (2009) *Going concern, ISA 570 in International Standards on Auditing*. Available: http://www.ifac.org/system/files/downloads/a031-2010-iaasb-handbook-isa-570.pdf (accessed on 30.06.2020).

Ivanickova M., Mihalcova B., Gallo P. (2016) Assessment of companies' financial health: comparison of the selected prediction models. *Actual Problems of Economics,* Vol. 180, No. 6, pp. 383–391.

Kaminski K., Wetzel T., Guan L. (2004) Can financial ratios to detect fraudulent financial reporting? *Managerial Auditing Journal*, Vol. 19, No. 1, pp. 18–28. DOI: http://dx.doi.org/10.1108/02686900410509802

Kanapeckiene R., Marcinkevicius R. (2014) Possibilities to apply classical bankruptcy prediction models in the construction sector in Lithuania. *Economics and Management,* Vol. 19, No. 14, pp. 317–332. DOI: http://dx.doi.org/10.5755/j01.em.19.4.8095

Kanapeckiene R., Grundiene Z. (2015) The model of fraud detection in financial statements by mean of financial ratios. *Procedia – Social and Behavioural Sciences*, Vol. 213, pp. 321–327. DOI: https://doi.org/10.1016/j.sbspro.2015.11.545

Lenard M., 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*, Vol. 1, No. 1, pp. 1–27. Available: https://www.semanticscholar.org/paper/An-Historical-Perspective-on-Fraud-Detection-%3A-From-Lenard-Alam/6d3645371b67be5df267ffc3e70ba1d5228a7226 (accessed on 30.06.2020).

Liodorova J., Voronova I. (2018a) Latvijas ekonomistu un juristu ieguldijums maksatnespejas novertejuma evolucija. *Proceedings of the International Scientific Conference "Social Sciences for Regional Development 2017"*, Daugavpils: Daugavpils Universitates Akademiskais apgads "Saule", 31.–42. lpp. Available: http://humanitiessocial.lv/strukturvienibas/socialo-petijumu-centrs/ zinatniskie-izdevumi/daugavpils-universitates-socialo-zinatnu-fakultates-starptautisko-zinatnisko-konferencu-rakstu-krajumi/ (accessed on 30.06.2020). (In Latvian)

Liodorova J., Voronova I. (2018b) Integral system of fraudulent bankruptcy evaluation. *Social Sciences Bulletin*, Vol. 27, No. 2, pp. 42–59. Available: https://du.lv/wp-content/uploads/2019/01/Liodorova.pdf (accessed on 30.06.2020).

Liodorova J., Mamikonyan K., Markina O. (2019) Comparative analysis of the methods of financial and economic examinations to determine insolvency. *Theory and Practice of Forensic Science and Criminalistics*, Vol. 20, No. 2, pp. 351–366. DOI: https://doi.org/10.32353/khrife.2.2019.27

Lukason O., Camacho-Minano M. (2019) Bankruptcy risk, its financial determinants and reporting delays: do managers have anything to hide? *Risks*, Vol. 77, No. 7, pp. 1–15. Available: https://www.mdpi.com/2227-9091/7/3/77/pdf (accessed on 30.06.2020).

Nia S. (2015) Financial ratios between fraudulent and non-fraudulent firms: Evidence from Tehran Stock Exchange. *Journal of Accounting and Taxation*, Vol. 7, No. 3, pp. 37–44. DOI: https://doi.org/10.5897/JAT2014.0166

Nguyen H. A., Nguyen H. L. (2016) Using the M-score model in detecting earnings management: Evidence from non-financial Vietnams listed companies. *VNU Journal of Science: Economics and Business*, Vol. 32, No. 2, pp. 14–23.

Pearsons O. (1995) Using financial statement data to identify factors associated with fraudulent financial reporting. *Journal of Applied Business Research*, Vol. 3, No. 1, pp. 38–46. DOI: https://doi.org/10.19030/jabr.v11i3.5858

Prusak B. (2018) Review of research into enterprise bankruptcy prediction in selected Central and Eastern European countries. *International Journal of Financial Studies*, Vol. 60, No. 6, pp. 2–28. DOI: https://doi.org/10.3390/ijfs6030060

Ragab Y. (2017) Financial ratios and fraudulent financial statements detection: evidence from Egypt. *International Journal of Academic Research*, Vol. 9, No. 4, pp. 1–6. Available: https://www.researchgate.net/publication/331772867_Financial_Ratios_and_Fraudulent_Financial_Statements_Detection_Evidence_from_Egypt (accessed on 30.06.2020).

Skiltere D., Zuka R. (2006) Latvijas uznemumu finansiala stavokla prognozesanas modelu statistiskais novertejums. *Latvijas Universitates raksti*, Nr. 706, 109.–124. lpp. (In Latvian)

Skiltere D., Zuka R. (2010) Approbation of the insolvency diagnosis models of the Latvian enterprises using the multivariate statistical methods. *Scientific Research*. Riga: Central Statistical Bureau of Latvia, pp. 260–275.

Sneidere R. (2007) *Finansu analizes metodes uznemuma maksatnespejas prognozesanai*. Promocijas darbs. Riga: Latvijas Universitate. (In Latvian)

Spathis C. (2002) Detecting false financial statements using published data: some evidence from Greece. *Managerial Auditing Journal*, Vol. 17, No. 4, pp. 179–191. DOI: https://doi.org/10.1108/02686900210424321

Spiciute A., Barkauskas M., Kuncevic M., Jansone A., Zeltite A., Liodorova J., Kangro I., Liivamae I. (2013) The economic expertise best practice guide for investigation of the crimes related to bankruptcy and for completion of the experimental insolvency research in the Baltic countries. Malevski H., Gorbatov A. (Eds.). *Forensic Methods*. Vilnius: Forensic Centre of Lithuania, pp. 62–122.

Stoskus S., Berzinskiene D., Virbickaite R. (2007) Theoretical and practical decisions of bankruptcy as one of dynamic alternatives in company's performance. *Engineering Economics*, Vol. 52, No. 2, pp. 26–33. Available: http://inzeko.ktu.lt/index.php/EE/article/view/11471 (accessed on 30.06.2020).

Wadhwa V., Saini A., Kumar S. (2020) Financial fraud prediction models: a review of research evidence. *International Journal of Scientific & Technology Research*, Vol. 9, No. 1, pp. 677–680. Available: http://www.ijstr.org/final-print/jan2020/-Financial-Fraud-Prediction-Models-A-Review-Of-Research-Evidence.pdf (accessed on 30.06.2020).

Appendix 1

Reviewed insolvency (bankruptcy) prediction models

Model	Year	Type of model	Model	Year	Type of model
Foreign models			Kralicek	1993	scoring index
Tamari	1966	scoring index	Irkutsk	1998	MDA
Altman 2-factors	1968	MDA	Savicka	2001	scoring index
Altman-Z	1968	MDA	Savicka	2001	MDA
Liss	1972	MDA	Slovak IN05	2005	MDA
Chesser	1974	logit/probit	Poland Cre-dibility index	2005	MDA
Argenti	1976	scoring index	Depalan	no data	scoring index
Tafflet / Tishaw	1977	MDA	**Latvian and Lithuanian models**		
Springate	1978	MDA	Sorin / Voronova, LV	1998	MDA
Olhson	1980	logit/probit	Grigaravicius, LT	2003	logit/probit
Altman-Z'	1983	MDA	Stoskus, LT	2007	–
Zavgren	1983	logit/probit	Muceniece / Lace, LV	2010	MDA
Zmijewski	1984	logit/probit	Skiltere / Zuka, LV	2010	scoring index
Fulmer	1984	MDA	Skiltere / Zuka, LV	2010	MDA
Altman-Z'	1993	MDA	Genriha / Pettere, LV	2010	logit/probit

Source: compiled by the authors.

Appendix 2

The abbreviations of the used items in the financial statements

Source	Item	Abbreviation	Item	Abbreviation
1	2	3	4	5
Balance sheet	Total assets	TL	Average total assets	*TA*
	Fixed assets	FA	Current assets	CL
	Plant, property & equipment	PPE	Equity	E
	Total liabilities	TL	Current liabilities	CL
	Funds borrowed in current liabilities	Debt in CL	Inventory	Inv
	Short-term investments	StInvest	Long-term liabilities	LtL
	Receivables	Rec	Cash	Cash
	Working capital = Current assets – Current liabilities	WC	Current payables of long-term debts and Income tax payable	CP
	Soft assets = TA – PPE – Cash	Soft		

Sequel to Table 2 see on p. 29

Sequel to Table 2

1	2	3	4	5
Profit or loss statement	Sales	S	Cost	Cost
	Net profit	NP	Earnings before interest and taxes	EBIT
	SGACost = Sales cost + General expense + Administrative expense	SGACost	Average monthly sales = Sales / Audited period (months)	S/t
	Interest expenses	%		
Other	Amortisation	Amort	Period	t
	Changes	Δ		

Source: compiled by the authors.