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BANKRUPTCY PREDICTION MODEL IN THE EXAMPLE OF ESTONIAN CONSTRUCTION COMPANIES

Master's thesis

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I have written this master’s thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced.

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Abstract

This paper aims to create a prediction model to distinguish between bankrupt and non-bankrupt Estonian construction companies. When composing the model, logistic regression analysis is applied. Financial ratios which are frequently used or have proved good predictive ability in different prediction models are included in composing the model. The composed model shows 68.4% overall classification accuracy and classifies correctly 74% of bankrupt companies one year prior to bankruptcy. The probability of bankruptcy decreases if return on total assets, cash ratio and equity ratio increase, indicating that construction companies that are more profitable relative to their total assets, have a higher ability to meet their short-term commitments and have a higher shareholders' equity relative to their total assets are less vulnerable to bankruptcy. The composed model outperforms Altman's *et al*. (2016) Z"-score logit model, which shows 62.8% overall classification accuracy on the same sample and classifies correctly 63.6% of bankrupt companies one year prior to bankruptcy.

Keywords: bankruptcy, prediction models, construction sector, logistic regression analysis

1. Introduction

The risk of business failure exists in every industry. The relatively low entry barrier, high level of competition and unpredictable fluctuations in construction volume make construction companies particularly vulnerable to business failure (Edum-Fotwe *et al.* 1996; Kale, Arditi 1999). According to Statistics Estonia, the construction sector made up 6% of the Estonian GDP in 2016. Construction companies form more than 9% of the total of Estonian companies and nearly 10% of employed persons operate in the construction sector. Throughout the years the number of bankruptcies per 1,000 companies has been one of the highest in the construction sector. Looking at all bankrupt companies in Estonia in 2016, the construction sector was on the second place with 3.63 bankruptcies per 1,000 companies (Pankrotid Eestis … 2017: 11).

According to the *Doing Business* (2016) report, the problem area of Estonian insolvency proceedings is the long duration of the proceedings, large number of bankruptcy proceeding abatements and low rate of creditor claim satisfaction compared to the OECD average. During 2015–2016 more than 60% of all insolvency proceedings in Estonia ended without declaration of bankruptcy because the debtor's assets were insufficient to cover the costs of bankruptcy proceedings (Pankrotid Eestis ... 2017: 5). Bankruptcy results in negative consequences not only for the company, its employees, state and society (Burksaitiene, Mazintiene 2011: 138) but can also trigger a domino effect and cause the insolvency of other companies (Wood 2012: 15). The significant importance of the construction sector in Estonian economy, the large number of bankruptcies and the negative consequences of bankruptcy cause the need to develop a bankruptcy prediction model based on a sample of construction sector companies. An early warning of impending financial distress enables the management and shareholders, lenders and auditors to take actions to reduce or avoid related costs (Keasey, Watson 1991: 89–90).

Bankruptcy prediction has been a challenging task in accounting since the 1930s (Back *et al*. 1996a: 1) and a major research topic in corporate finance (Balcaen, Ooghe 2006: 64). A number of academic studies are conducted to find the best prediction model that can classify companies according to their financial standing (*Ibid.:* 86). Studies on the development of bankruptcy prediction models include the univariate analysis model (Beaver 1966), multiple discriminant analysis (Altman 1968; Deakin 1976; Taffler 1982), conditional probability models such as logit (Ohlson 1980), probit (Zmijevski 1984) and linear (Meyer, Pifer 1970) probability models, as well as popular machine learning techniques such as neural networks (Tam, Kiang 1992; Zhang 1999) and genetic algorithms (Back *et al*. 1996b). The classical cross-sectional statistical methods have been widely used for developing failure prediction models and they involve a certain procedure to classify firms into a failing or a non-failing group with a certain degree of accuracy or misclassification rate (Balcaen, Ooghe 2004: 5). Due to differences between the construction sector and other sectors, these studies may lack the ability to assess the construction sector accurately.

Bankruptcy prediction models have also been developed based on the construction sector of different countries, e.g. the UK (Mason, Harris 1979; Hall 1994; Abidali, Harris 1995), the USA (Kangari 1988; Russell, Jaselkis 1992; Adeleye *et al*. 2013), Russia (Makeeva, Neretina 2012), Portugal (Vieira *et al*. 2013) and Italy (Muscettola 2014). More country-based construction sector prediction studies have been made since the beginning of the 1990s. Nevertheless, construction sector studies are often focused on explaining failure at the project level rather than the company level (Koksal, Arditi 2004). Many construction studies only assess the performance of existing models without developing any improved models, like studies in the example of the construction sector in Lithuania (Marcinkevičius, Kanapickiene 2014) and Romania (Bărbută-Misu, Codreanu 2014). Some of the studies assess the classification performance of a model on the small estimation sample or even on the basis of few companies.

This paper aims to create a prediction model to distinguish between bankrupt and non-bankrupt Estonian construction companies. When composing the model, the logistic regression analysis is applied. Financial ratios which are frequently used or have indicated good predictive ability in different prediction models are included in composing the model. Additionally the performance of the Z“-score LR model (Altman *et al*. 2016) and Holdt’s (2015) model based on the Estonian construction industry will be assessed.

This thesis uses data of Estonian construction company population available from the Centre of Registers and Information Systems. The initial sample consists of 13,388 companies, containing 13,104 operating and 284 bankrupt companies, which have gone bankrupt in 2013–2016. In the case of bankrupt companies, the financial data (balance sheets, income statements, hereinafter abridged as *annual reports*) of one year before bankruptcy are observed. In the case of operating companies, the initial sample includes all of the operating firms and their financial data is from the 2011–2014, which is the same period as that of the bankrupt companies. The number of bankrupt companies includes permanent insolvencies declared by a court ruling as well as termination of bankruptcy proceedings by abatement without declaration of bankruptcy.

This paper is structured as follows. Literature review in section two involves two major subjects: bankruptcy as a type of business failure and review of construction firm specific and non-construction firm specific bankruptcy prediction models. Section three describes the data and methodology of the statistical analysis used in the empirical study. The fourth section presents the results of the statistical analysis. The last section consists in the concluding remarks of the paper.

2. Literature review

2.1. Bankruptcy as a type of business failure

There is great variety in bankruptcy prediction models and the academic research on business failure is extensive (Balcaen, Ooghe 2006: 63; Bellovary *et al*. 2007: 1). An important issue in comparing different prediction models is the fact that the separation of failing and non-failing firms is often arbitrary, including the definition of failure itself and the year or time period in which the failure definition is applied (Balcaen, Ooghe 2006: 73). In a broad sense, a company will be considered failed if it does not meet the objectives set forth by its management (Sharma, Mahajan 1980: 81). The narrowest concept of failure is to equate it with formal bankruptcy (Cochran 1981: 52). In some academic studies the definition of failure is extended to different kinds of losses to creditors, which include bankruptcy but also voluntary withdrawal, leaving behind unpaid obligations and voluntary compromise with creditors (*Ibid.*). Although many studies use the definition of failure prediction, these studies are often limited to the bankruptcy prediction, which means that only the narrowest subset of business mortality is analyzed (*Ibid.*). Karels and Prakash (1987: 575) point out that bankruptcy is a process which begins financially and is consummated legally.

Pursuant to the Estonian Bankruptcy Act the bankruptcy means the insolvency of a debtor declared by a court ruling (Bankruptcy Act, § 1). A debtor is insolvent if the debtor is unable to satisfy the claims of the creditors and such inability, due to the debtor's financial situation, is not temporary (*Ibid.*), which refers to cash-flow insolvency. A debtor who is a legal person is considered to be insolvent also if the assets of the debtor are insufficient for covering the obligations thereof and, due to the debtor's financial situation, such insufficiency is not temporary (*Ibid.*), which refers to balance sheet insolvency. The cash flow test, sometimes combined with the balance sheet test, is the most common criteria for initiating full insolvency proceedings in almost all EU member states (Bariatti, van Galen 2014: 28). The cash flow test requires that the debtor has generally ceased making payments and will not have sufficient cash flow to service its existing obligations as they fall due in the ordinary course of business, whilst the balance sheet test concerns an excess of liabilities over assets as an indication of financial distress (*Ibid.*).

In this paper failure is equated to the permanent insolvency declared by a court ruling (bankruptcy), which is in accordance with the approach of many academic studies. The popularity of the legal definition of failure provides an objective criterion that allows the companies to be easily separated into two groups and provides for objective determination of the moment of failure (Ooghe, Balcaen 2006: 72).

2.2. Review of a bankruptcy prediction models

Bankruptcy prediction studies started with search for empirically best predictors (i.e. financial ratios). The early studies for bankruptcy prediction were univariate studies which focused on individual ratios and compared the ratios in the group of failed and non-failed companies (Bellovary *et al*. 2007: 2). The subsequent multivariate studies are based on the groundwork of univariate studies (*Ibid.*); however, simultaneously the multivariate studies concentrate on the search for the best statistical methods applicable to financial ratios. Although there are many studies of company failure prediction models (Beaver 1966; Altman 1968; Edmister 1972; Deakin 1972; Ohlson 1980), the research topic is still under-explored in the context of the construction industry (Wong, Ng 2010: 1; Tserng *et al*. 2015: 121). Previous studies indicate that some failure prediction models might be widely usable, because applying to the sample a completely different from the original estimation sample, they indicate high predictive performance (Ooghe, Balcaen 2007: 61-62) which enables them to be used on other samples in the same industry or even on a sample of other industries. At the same time, some of the models present very poor results and therefore cannot be considered to be widely applicable (*Ibid.*). It can be explained with the fact that firms in different industries have different strategies (Thornhill, Amit 2003: 505), different levels of competition and different accounting regulations (Chava, Jarrow 2004: 538; Tserng *et al*. 2015: 121). The economic environment and country-specific legislation also may affect the financial behaviour and the boundary between bankrupt and non-bankrupt firms (Altman *et al.* 2016: 15). As bankruptcy prediction models are based on specific sectors, samples and periods, it remains a challenge to increase the predictive accuracy on other samples.

2.2.1. Ratio analysis and financial ratios used in bankruptcy prediction models

Traditional ratio analysis involves calculating single ratio values by using any two financial figures and provides a very quick and effective way of obtaining an insight into a company's performance. Beaver's (1966) pioneering study presented the univariate approach which is the most widely recognized single-factor study. The application of the univariate analysis requires minimal statistical knowledge and its application is relatively simple as it compares the value of the financial ratio with a cut-off point and determines the classification accordingly (Balcaen, Ooghe 2006: 65).

In his study, Beaver (1966) compared the mean values of 30 ratios of 79 failed and 79 non-failed firms in 38 industries and tested the individual ratios' predictive ability in classifying bankrupt and non-bankrupt firms. In this study, the following variables were found useful to distinguish between the bankrupt and non-bankrupt companies (*Ibid.*: 78-79):

1) Cash flow/ Total debt,
2) Net income/ Total assets,
3) Total debt/ Total assets,
4) Working capital/ Total assets,
5) Current assets/ Current liabilities,
6) No credit interval = (Quick assets – Current liabilities)/ (Operating costs – Depreciation).

Each ratio was analyzed separately and the cut-off point was selected to maximize the classification accuracy for a specific sample. Cash flow/ Total debt had the highest predictive ability – 90% accuracy one year prior to failure. In his study, Beaver conceded a possibility that multiple ratios considered simultaneously may have higher predictive ability than single ratios.

Chan *et al*. (2005) adopted the single-factor analysis to assess the financial performance of construction companies in Hong Kong with a purpose of formulating appropriate strategies for the companies. During the study the values of financial ratios of eight large contractors in 1997–2002 were analyzed. The determining factors of business failure were operating profit margin, return on equity, return on asset, total asset turnover, quick ratio, earning per share and debt ratio. Huang (2009) investigated 10 defaulting and 30 non-defaulting construction companies in Taiwan in 1999–2006. The results indicated that the determining factors of business failure, among others, are asset volatility, book leverage ratio and the price-to-earnings (P/E) ratio.

Subsequent studies have criticised the univariate approach, since using a single financial ratio is not a sufficiently reliable way to predict failure (Bal *et al*. 2013: 3). Based on earlier studies, Bellovary *et al*. (2007) noticed that more than 752 different variables were used in the previous studies, and 22 of these were applied ten or more times in different studies (*Ibid.*: 42).

The financial ratios can be listed in four different ratio categories, involving (Edum-Fotwe *et al*. 1996: 190):

1) Liquidity ratios which measure a company's ability to meet its short-term commitments,
2) Profitability ratios which measure the overall performance or returns the management has been able to achieve,
3) Leverage ratios which measure the extent to which a company has been financed by debt and shareholders' funds,
4) Activity ratios which measure how well a company has been using its resources.

Different authors divide financial ratios differently, using three categories (Back *et al.* 1996a: 10) or more than four categories of ratios (Altman 1983: 594; Bal 2013: 4;

Makeeva, Neretina 2013: 261). The financial ratios used in this study are classified in abovementioned four categories and presented in section three.

2.2.2. Multiple discriminant analysis

The best known and most popular bankruptcy model was developed by Altman (1968) by using a multiple discriminant analysis (MDA); the model is known as a Z′-score, initially developed for manufacturing companies. The main idea of MDA is to combine the information from several financial ratios into a linear discriminant function. Each firm receives a single composite discriminant score which is compared to a cut-off value which determines to which group the company belongs (Back *et al*. 1996a: 2).

The Z′-score model was developed on the basis of 66 large companies, involving 33 non-bankrupt and 33 bankrupt companies. The model had 95% overall accuracy on the estimation sample one year before failure, but two years before failure it shows only 72% predictive ability. By eliminating one of the initial variables in order to minimize the potential industry effect, in 1983 the modified Z″-score for non-manufacturing companies was developed (Altman 1983). Since Altman's (1968) initial Z′-score model was intended for publicly traded firms, in Z″-score model (Altman 1983) the *market value of equity* was exchanged for *book value of equity*. Both of Altman's models are presented in table 1.

Table 1. Formula, variables and classification of Altman's models based on multiple discriminant analysis

	Z′-score (1968)	**Z′′-score (1983)**
Formula	$Z = 1{,}2X_1 + 1{,}4X_2 + 3{,}3X_3 + 0{,}6X_4 + 0{,}999X_5$	$Z = 3{,}25 + 6{,}56X_1 + 3{,}26X_2 + 6{,}72X_3 + 1{,}05X_4$
Variables	X_1 = Working capital/ Total assets X_2 = Retained earnings/ Total assets X_3 = Earnings before taxes and interest/ Total assets X_4 = Market value of equity/ Book value of total debt X_5 = Sales/ Total assets	X_1 = Working capital/ Total assets X_2 = Retained earnings/ Total assets X_3 = Earnings before taxes and interest/ Total assets X_4 = Book value of equity/ Book value of total debt
Classification	> 2.99 - non-bankrupt < 1.81 - bankrupt 1.81 – 2.99 – *zone of ignorance* or *grey zone*	> 2.6 - non-bankrupt < 1.1 - bankrupt 1.1 – 2.6 – *zone of ignorance* or *grey zone*

Source: Compiled by the author based on Altman (1968), Altman (1983).

Although MDA assumes the dependent variable to be dichotomous (Balcaen, Ooghe 2006: 67), and thus, the populations of failing and non-failing firms are expected to be clearly separated from each other, it appears on the basis of Altman's MDA models that due to the *grey zone* no clear distinction between failing and non-failing companies can be made. Consequently, interpretation of the discriminant score is complicated.

Mason and Harris (1979) recognized that earlier failure models, developed primarily based on retail or financial sector, might not be suitable for application to construction companies, since the industry factors may affect the prediction models. They developed a six-variable model for evaluating UK construction companies. Differently form Altman's discriminant score, they presented the dependent variable as dichotomous – a positive Z-score indicated a long-term solvency, whilst a company with a negative value was classified as being potentially insolvent. Abidali and Harris (1995) developed a model to predict UK construction company failure using seven financial ratios and 13 managerial factors. They showed that non-financial indications of insolvency appear a lot earlier than financial distress (*Ibid.*).

In addition to these two models which constitute frequently referred MDA models based on construction companies, there are several studies in the construction sector that used the multiple discriminant analysis (e.g. Langford *et al.* 1993; Bal 2013; Makeeva, Neretina 2013; Bărbută-Misu, Codreanu 2014). However, some of the studies only assess the performance of the models developed earlier by different researchers (e.g. Bărbută-Misu, Codreanu 2014).

MDA is based on three restrictive assumptions (Edmister 1972; Eisenbeis 1977; Karels, Prakash 1987): (1) the independent variables included in the model are multivariate normally distributed, (2) the group dispersion matrices are equal across the failing and the non-failing group and (3) the prior probability of failure and the misclassification costs are specified. Empirical studies have shown that especially failing firms violate the normality condition (Back *et al.* 1996a: 2). It has been emphasized that in practice, the data rarely satisfies the three statistical assumptions, the MDA modeling technique is often applied in an inappropriate way, and thus, conclusions and generalizations are questionable (Joy, Tollefson 1975; Eisenbeis 1977). A non-dichotomous classification of the discriminant score makes the application of MDA even more problematic.

2.2.3. Logistic regression analysis

Logistic regression analysis (logit analysis) is one of the conditional probability models next to the probit and linear probability models. All the conditional probability models allow the use of the non-linear maximum likelihood method to estimate the probability of failure conditional on a range of firm characteristics (Balcaen, Ooghe 2006: 68). As does the MDA, the logit model assumes the dependent variable to be dichotomous (*Ibid.*: 69).

Logit analysis creates a score (logit) L for every firm. The logit score implies the probability of failure and is presented as value between 0 and 1, where the failed status is usually coded as 1 and non-failed status as 0. A high logit score indicates a high failure probability and accordingly, a poor financial health (Balcaen, Ooghe 2006: 69). Altman *et al*. (2016) indicated that the cut-off value that best separates failures from non-failures is 0.50. The logit score is used to determine the conditional probability of failure as follows (*Ibid.*):

(1) $$p(Y = 1|X) = \frac{1}{1+e^{-L}} = \frac{1}{1+e^{-(b_0+b_1X_1+\ldots+b_nX_n)}}$$

where b_i (i= 0, …, n) are the coefficients and X_i (i= 1, …., n) are the independent variables of the model.

The logit model assumes a logistic distribution while the probit model assumes a cumulative normal distribution (Balcaen, Ooghe 2006: 68). The main advantages of the logit model compared to MDA consists in the fact that the logit model makes neither the assumption on multivariate normality, equal covariance matrices (Ohlson 1980), nor the distributional assumptions for distributional variables (Balcaen, Ooghe 2006); also, the categorical qualitative variables are allowed (Keasey, Watson 1987). As logit analysis does not require the restrictive assumptions of MDA and allows work with disproportional samples, the logit analysis is commonly considered as less demanding than MDA. The main drawback of the logit model the extreme sensitivity to multicollinearity, extreme non-normality of independent variables, outliers and missing values has been emphasized (Balcaen, Ooghe 2006: 69).

Among the first users of logit analysis in the context of financial distress was Ohlson (1980). His model, known as an O-score, was developed as an alternative to the Altman´s

(1968) Z′-score and included over 2,000 companies. The model involved 9 different variables and the model´s accuracy both one and two years before the bankruptcy was 96% (*Ibid.*: 121).

Altman *et al.* (2016) reviewed the Altman's (1983) Z″-score model and re-estimated it using logit analysis which is based on less-restrictive statistical assumptions than MDA. When preparing the model, Altman *et al.* (2016) included data from 31 European countries, including Estonia, and three non-European countries (China, Colombia and the United States). Observations of the companies are from 2007–2010 and only companies whose total assets exceeded 100,000 euros at least once during the observed time period were included. The variables in this model were the same as in the Altman's (1983) Z″-score model. During the revision, Altman *et al*. (2016) composed eight different logit models, varying the models with different dummy variables, e.g. year, size, age, industry and country risk. Save for the construction sector, industry specific dummies were calculated (e.g. for restaurants and hotels, agriculture and manufacturing companies). The revised model is called the Z″-score LR model. Table 2 presents Z″-score LR model and Z″-score LR model including a dummy variable for the construction sector.

Table 2. Formula and variables of Z″-score LR models

	Z″-score LR model	**Z″-score LR model including dummy variable for the construction sector**
Formula	$Z = 0.035 - 0.495X_1 - 0.862X_2 - 1.721X_3 - 0.017X_4$	$Z = 0.048 - 0.540X_1 - 0.859X_2 - 1.695X_3 - 0.016X_4 + 0.445X_5$
Variables	X_1 = Working capital/ Total assets X_2 = Retained earnings/ Total assets X_3 = Earnings before taxes and interest/ Total assets X_4 = Book value of equity/ Total liabilities X_5 = Dummy variable for the construction industry	

Source: Altman *et al*. (2016), compiled by the author.

It is noteworthy that in predicting bankruptcies, the overall classification accuracy of the Z″-score LR model (2016), which includes a dummy variable for the construction sector, was 83.3% as relating to Estonian companies, assessed on the estimation sample by the Area Under Curve (AUC). Such accuracy was one of the highest among the included countries. The classification accuracy of the model as relating to others countries' data was between 65.9% (in Bulgaria) and 98.7% (in China) and the accuracy was higher than in Estonia only in four countries (Bosnia, China, Finland and Poland). The Z″-score LR model without a dummy variable for the construction sector also proved high accuracy as relating to Estonian companies – 82.3% on estimation sample, assessed by the AUC.

Although a number of country-specific construction studies are based on the logit analysis, these studies are considered to have some drawbacks, e.g.:

1) small estimation sample, involving less than 60 companies (e.g. Russell, Jaselkis 1992; Hall 1994; Koksal, Arditi 2004; Huang 2009), making generalization complicated;
2) models partially involve non-financial variables, usually not obtainable from annual reports (e.g. Hall 1994; Abidali, Harris 1995), decreasing the models' application in practice. Usually an accounting-based approach is the only solution applicable by banks and lenders (Altman *et al.* 2016: 10);
3) the studies test known models and assess their classification performance, yet no improved model is composed with an aim of increasing the classification accuracy (e.g. Marcinkievičius, Kanapickiene 2014), allowing to draw only limited conclusions about models with the best predictive ability. Altman *et al*. (2016), when revising Altman's (1983) Z″-score showed that even only re-estimation of the coefficients of the variables may lead to the improved classification accuracy of the model.

There are only a few single studies conducted in the construction sector based on logit analysis in which a completely new model was developed, e.g. in Portugal (Vieira *at al*. 2013), Italy (Muscettola 2014), and Estonia (Holdt 2015). None of these studies tested any previous models.

The sample based on Portuguese companies included a total of 150 bankrupt companies and 150 operating companies. In this model financial data for the time period of up to four years prior to bankruptcy was observed and a separate model was developed for each year. Initially, eight different variables were included in the model, from which up to four remained in the final models. The determining factors of failure one year prior to bankruptcy were Cash flow/ Total assets and Sales/ Total assets. Classification accuracy of the model one year prior to bankruptcy was 81.74%.

In Holdt's (2015) model based on the Estonian construction sector, 62 bankrupt and 150 operating companies were involved. The composed logit model included two different financial ratios and showed the overall classification accuracy of 98.1% on estimation sample and of 82% on validation sample one year prior to bankruptcy. Holdt's model can be presented as follows (*Ibid*.: 35):

$$L = -6.327 + 3.007X_1 + 0.163X_2 \quad (3)$$

where X_1 is Total liabilities/ Total assets and X_2 is Net sales/ Total assets.

After composing a new model, this study will also assess the performance of Z′′-score LR model (Altman *et al*. 2016) and Holdt's (2015) model because of their high classification accuracy level. Determining factors when choosing the models were also access to the necessary financial data and simplicity of model application depending on it. Although Altman's (1983) Z′′-score model based on multiple discriminant analysis has been widely used, the Z′′-score LR model (Altman *et al*. 2016) based on logistic regression analysis is rather novel and it has not been tested on the example of Estonian construction companies. According to the author's knowledge, it has not been tested with other countries' construction sector companies either.

3. Data and method

This thesis uses data of Estonian construction company population available from the Centre of Registers and Information Systems. Construction companies are companies that, according to the Statistical Classification of Economic Activities in the European Community (NACE) 2008, belong to division F and operate in the field of construction of buildings (NACE 41), civil engineering works (NACE 42) and specialised construction activities (NACE 43).

The initial sample consists of 13,388 companies, containing 13,104 operating and 284 bankrupt companies, which have gone bankrupt in 2013–2016. In the case of bankrupt companies, the annual reports of one year prior to bankruptcy are observed. In the case of operating companies, the initial sample includes all the operating firms and their financial data is from 2011–2014, which is the same period as that of the bankrupt companies. Data on the bankrupt companies is available from the Centre of Registers and Information Systems database. Table 3 provides data for the general population of

Estonian construction companies and bankrupt construction companies during 2013–2016.

Table 3. General population of construction companies and bankrupt construction companies in Estonia during 2013–2016

Year	Population of construction companies (end of the year)	Number of bankrupt companies	Bankruptcies per 1 000 companies
2013	18 424	79	3.85
2014	17 842	64	3.87
2015	18 424	71	3.85
2016	19 274	70	3.63

Source: Compiled by the author based on Pankrotid Eestis ….. 2016, Pankrotid Eestis ….. 2017, Centre of Registers and Information Systems.

Considering the nature of this study, binary logistic regression analysis was applied. Logit models make an assumption on clear distinction between operating and bankrupt firms (Balcaen, Ooghe 2006: 69). Since bankrupt companies have been clearly defined, it is important to also specify operating firms. A company is operating if it is financially active and there is no bankruptcy declared regarding it. Based on the aforementioned, companies that did not have any net sales or that had zero total assets were removed from the initial operating companies sample. The majority of Estonian construction companies are micro and small enterprises, therefore the firms with total assets or net sales greater than 10 mln euros were discarded from the sample. Due to the nature of logistic regression analysis which eliminates observations with missing values, all the annual reports that lacked data necessary for analysis were discarded from the sample.

When composing a bankruptcy model, several studies involve only companies that have an annual report for the year prior to bankruptcy (Beaver 1966; Altman 1968; Ohlson 1980; Altman *et al*. 2016). In practice, such an approach may cause problems because many firms do not submit an annual report for the year prior to bankruptcy. On the other hand, elimination of such companies may cause the sample of bankrupt firms to decrease significantly. However, there are models that use earlier data (Dimitras *et al*. 1996; Bellovary *et al*. 2007). This study uses both approaches and the most recent available financial statements are observed, except the reports submitted less than six months before declaration of bankruptcy. This means that if a company went bankrupt within a period of six months after the end of the financial year, the financial data of two year before bankruptcy were used. If a company went bankrupt within a period of 6–12 months after the end of the financial year, the financial data of one year before bankruptcy were used. Firms with latest financial data older than two years from the date of bankruptcy were discarded from sample. Such an approach is in compliance with earlier bankruptcy prediction studies.

After all the described eliminations, the size of the final sample was 7,160 companies, including 7,083 operating and 77 bankrupt firms. In the case of bankrupt companies, the annual reports of one year before bankruptcy were observed. In the case of operating companies, the final sample includes all of the operating firms and their annual reports for one or several years. The total number of observed annual reports was 13,902, including 13,825 annual reports of operating firms and 77 annual reports of bankrupt firms. Variables used in modeling were calculated based on the financial data provided in the annual reports and are described in table 4.

Table 4. Financial ratios used in the modeling

Financial ratios and their frequency in previous studies	Ratios in SPSS	Altman	Holdt	Additional ratios
Profitability				
Retained earnings/ Total assets (42)	RETA	X		
Earnings before interest and taxes/ Total assets (35)	EBITTA	X		
Net income/ Net sales (9)	NINS			X
Liquidity				
Current assets/ Current liabilities (51)	CACL			X
Working capital/ Total assets (45)	WCTA	X		
Cash/ Current liabilities (26)	CASHR			X
Leverage				
Total liabilities/ Total assets (19)	TLTA		X	
Book value of Equity/ Total liabilities (16)	BVETD	X		
Shareholders' Equity/ Total Assets (N/A)	EQRATIO			X
Activity				
Net sales/ Total assets (32)	NSTA		X	
Net Sales/ Current assets (N/A)	NSCA			X

Source: Compiled by the author. Financial ratios are based on categories by Edum-Fotwe *et al.* (1996) and categorized according to Bal *et al.* (2013), Makeeva and Neretina (2013). The frequency of studies is based on Bellovary *et al.* (2007). N/A implies unavailability of the number of previous studies.

Considering the lack of necessary data in relevant annual reports, some of the initially chosen variables were discarded from the final analysis to avoid decreasing the estimation sample of bankrupt companies. These ratios are not presented in the table.

In literature, ratios are usually selected on the basis of their popularity and combined with a few new ratios selected by the researcher (Barnes 1987). In this paper, the selection of financial ratios is based on the frequency of their use in earlier studies (Bellovary *et al.* 2007: 42) and their good predictive ability in different construction sector models. Literature based popularity was the basis for selecting variables in 40% of previous studies (Jardin 2009: 8). Besides the variables used in the Z``-score LR model (Altman *et al*. 2016) and Holdt's (2015) model, some additional variables were involved and the expanded set of variables was created.

Approximately 65% of observed income statements lacked the data of interest revenue and interest expenses, which are necessary for calculating EBITTA (Earnings before interest and taxes/ Total assets). Using the available financial data of 35% of observed income statements, the correlation coefficient between EBIT and operating profit was 0.74. In light of above, in this paper operating profit is used as a proxy to EBIT, and Operating profit/ Total assets is used as a proxy to EBITTA.

Previous studies indicate that the distribution of financial ratios tends to be non-normal (Eisenbeis 1977: 896; Karels, Prakash 1987: 581, Barnes 1987: 450). Since the logit models do not require the variables to be normally distributed (Balcaen, Ooghe 2006: 70; Altman *et al.* 2016: 11), applying logit analysis is justified. Considering the logit models' sensitivity to extreme values and outliers, the independent variables used by modeling were winsorized at 1% and 99%, which means that an outlier's value is changed to that of the closest non-outlier (Barnes 1987: 451). Above technique is in accordance with the approach of many academic studies (e.g. Altman *et al.* 2016; Cantrell *et al*. 2014). Although the distribution of financial ratios is rather non-normal, the values of skewness and kurtosis were analyzed to identify the distribution's shape.

The proportions of observations of bankrupt companies (77 observations) and operating companies (13,825 observations) are not equal in the final sample. During modeling, the equality of influence from the companies of both groups must be ensured to avoid non-proportional sampling from operating companies. To correct disproportional sample sizes, data weighting is usually applied which means that failed and non-failed firms get equal weights in estimation, whereas the number of observations is set equal to the original size of the estimation sample (13,902 observations). Considering the final sample size and the proportion of annual reports in the sample, the weighting factor (W) for each company was calculated as follows:

$$W = \frac{0.5}{proportion\ of\ the\ observations\ in\ the\ final\ sample} \tag{4}$$

As a result, if a company is operational, the proportion of observations in the final sample is $\frac{13825}{13902}$ = 0.994461, and thus, the weighting factor is 0.5028. If a company is bankrupt, the proportion of observations in the final sample is $\frac{77}{13902}$ = 0.005538 and the weighting factor is 90.2727. The same approach for data weighting has been used in many studies, e.g. by Laitinen and Suvas (2013) and Altman *et al*. (2016).

Based on selected variables a new logit model for the period of one year prior to bankruptcy was composed. Initially, all 11 financial ratios presented in table 4 were selected for bankruptcy prediction. To examine which variables may have the best predictive ability, the Independent Samples Median Test was chosen. It tests the null hypothesis that the medians for two groups are equal for each variable.

When composing the model, different stepwise logistic regression selections (*Enter, Forward Selection, Backward Elimination*) were applied first. As a result, the initially composed different models consisted of relatively high number of variables, including strongly correlated financial ratios. First, such an approach causes problems with multi-collinearity and, secondly, a high number of variables makes interpretation of the models complicated. Instead of using stepwise selections, the following process was applied when composing the model. Considering that every financial ratio separately may have predictive ability to a certain extent (Altman 1968: 594; Pompe, Bilderbeek 2005: 864), the classification ability of each variable was first assessed separately to determine which variables to include in or drop from the model. The variables that stand out with best predictive ability in every category were included in the model. Thereafter the variables were exchanged for other variables of the same category if it helped to improve the model's classification accuracy and if the new variable was statistically significant. At the same time the values of the Cox & Snell R square, Nagelkerke R square and the likelihood-ratio were estimated, to assess the goodness of the fit of the model. Such a method was applied repeatedly in different combinations of financial ratios with the aim of finding a model which is the most appropriate and reliable combination of high classification accuracy and explained variance of the model.

In literature, both estimation sample and validation sample are used to evaluate the predictive ability of bankruptcy models. Using a validation sample means that validity is obtained through the use of a hold-out sample which is a separate set of observations and is able to acquire a stronger measure of the model's predictive accuracy (Bellovary *et al*. 2007: 7-8). It has been noted that many studies do not use a validation sample (*Ibid.*: 8). Although these models may have the maximum classificatory success within the sample, they show reduced accuracy outside of the estimation sample (Abad *et al*. 2007). Applying a validation sample is acceptable and often required if the sample size is small (Bellovary *et al*. 2007). The composed model already uses the general population data of construction companies; therefore separating the data for validation sample is not vital. Since the number of bankrupt companies in the estimation sample was 77, the compilation of a validation sample would reduce the bankrupt companies' sample and would increase the chance of a statistical error.

Still, to assess the performance of the composed model outside of the estimation sample, this study uses a validation sample from a similar economic cycle (2001–2003) to avoid the potential influence of economic recession. Previous studies indicate that the accuracy and structure of predictive models differ across different economic cycles (Mensah 1984: 393) and that characetristics of bankrupt companies in particular can be affected when applying the model in different economic cycles (Grünberg 2013: 45). The validation sample consists of 3,996 companies, containing 3,940 operating and 56 bankrupt companies, which went bankrupt in 2003–2004. The total number of observed annual reports in the validation sample was 8,498. In the case of bankrupt companies, the annual reports of one year before bankruptcy were observed. In the case of operating companies, the validation sample includes all of the operating firms and their financial data is from the 2001–2003 (one or several years), the same period as that of the bankrupt companies.

Analysis was carried out with SPSS Statistics 24. Multicollinearity diagnostics was carried out in Stata 13. After composing a new model, the performance of the Z``-score LR model (Altman *et al*. 2016) and Holdt's (2015) model was assessed.

4. Results and discussion

Table 5 presents descriptive statistics of all initially included variables. The Independent Sample Median Test (ISMT) shows that the medians for the failed and non-failed groups are statistically significantly different (ISMT p-value less than 0.05) for all included variables, except the efficiency ratio Net sales/ Current assets (NSCA). It can be concluded that all of the variables, except the NSCA, may have predictive ability and can be used in modeling.

Table 5. Descriptive statistics

	Median		Mean		Std. Deviation		ISMT p-values
	Non-failed	Failed	Non-failed	Failed	Non-failed	Failed	
RETA	0.446	0.153	0.373	-0.138	0.417	1.156	0.000
EBITTA	0.078	0.010	0.083	-0.377	0.354	1.336	0.000
NINS	0.035	0.002	-0.039	-0.218	0.575	0.661	0.000
CACL	2.018	1.173	2.723	1.672	2.069	1.425	0.000
WCTA	0.357	0.109	0.328	-0.820	0.352	0.863	0.000
CASHR	0.689	0.664	1.340	0.324	1.607	0.588	0.000
TLTA	0.767	0.762	0.802	1.037	0.126	1.121	0.000
BVETD	1.458	0.311	2.383	0.894	2.479	1.814	0.000
EQRATIO	0.593	0.237	0.530	-0.037	0.306	1.121	0.000
NSTA	2.100	2.572	2.424	3.056	1.702	2.538	0.000
NSCA	3.170	3.066	3.525	3.745	2.225	2.846	0.192

Source: compiled by the author.

In literature it has been emphasized that most of the financial ratios tend to be positively skewed (Deakin 1976; Frecka, Hopwood 1983; Barnes 1987) which means that usually the right tail (larger values) of the shape is much longer than the left tail (small values). To exclude the risk of outliers and ensure the reliability of descriptive statistics, skewness and kurtosis of the variables were estimated to identify the shape of the distribution. Analysis showed that although the skewness and kurtosis of some variables were inherent to normal distribution, some other variables were moderately skewed and remained non-normally distributed. In light of above, a certain pattern related to the skewness of the variables cannot be revealed. This is in conformity with the previous studies which indicate that even after removing the outliers the financial ratios were still found to be non-normally and asymmetrically distributed (Barnes 1987: 452).

For variables in the profitability, liquidity and leverage categories, the medians of the ratios are higher in the group of non-failed firms, which is in line with the expectations. As an exception, Total liabilities/ Total Assets (TLTA), expected to be higher among failed companies, is higher in the group of non-failed firms.

For activity ratio Net sales/ Total assets (NSTA) the median was higher in the group of failed firms. Normally, the asset turnover ratio is considered to indicate better performance of the company and a higher ratio refers to the efficiency of the company in using its assets to generate revenue. However, it should be stressed that asset turnover ratio can vary widely between the sectors as well as within the same sector, depending on how fixed asset-intensive the company´s business is. The size of the asset turnover ratio is influenced by asset purchases in the growth-phase of the company and, otherwise, upon selling unnecessary assets. The higher asset turnover ratio in the construction sector may therefore characterize the companies that use their resources well, yet may also be inherent to companies that have relatively higher turnover, yet at the same time remarkably lower total assets. On the other hand, the size of total assets is influenced by the age of the fixed tangible assets as well as the amortization method which also explains the differences within the sector. A lower asset turnover ratio may also indicate that the company is working very close to the limit of its capacity (Altman 1983). In light of above, it can be concluded that bankrupt companies tend to invest less (e.g. machinery, buildings, land etc.) and are focused on less fixed asset-intensive construction works.

In the further process, all financial ratios (except Net sales/ Current Assets which showed no statistically significant difference between the groups) were included in modeling. The further process for selecting the financial ratios into the final model was described in section three (see p. 19). The variables in the final model and estimations of the parameters are presented in table 6.

Table 6. Variables in the final model and multicollinearity diagnostics

Variable	B	S.E.	Wald	Df	Sig.	Exp(B)	VIF
EBITTA	-0.221	0.038	33.859	1	0.000	0.802	1.16
CASHR	-0.733	0.029	658.736	1	0.000	0.480	1.40
EQRATIO	-1.158	0.063	336.917	1	0.000	0.314	1.55
Constant	0.876	0.030	848.701	1	0.000	2.402	

Source: compiled by the author.

The Wald test which works by testing the null hypothesis that a set of parameters is equal to some value (which is not zero) indicates that none of the values are equal to zero. It indicates that the parameters are statistically significant and should be included in the model. The VIF values for all parameters are less than 3 which indicates that there is no multicollinearity in the model. The final model consists of financial ratios of profitability (EBITTA), liquidity (CASHR) and leverage (EQRATIO) categories. As including efficiency ratios (NSTA and NSCA) did not improve the model's classification accuracy, the efficiency ratios are not involved in the final model.

In this study, the cut-off value to separate non-failed and failed companies is 0.50 which means that a company with a probability of 0.50 or higher is classified as bankrupt and a company with a probability smaller than 0.50 is classified as non-bankrupt. Table 7 shows the classification accuracy of the composed model.

Table 7. The goodness of fit of the model and classification accuracy

Measure of the performance	Indicator	Value
Goodness of fit of model	-2 Log likelihood	15730.137
	Cox & Snell R Square	0.231
	Nagelkerke R Square	0.308
Classification accuracy	Sensitivity	74.0%
	Specificity	62.7%
	Overall	68.4%

Source: compiled by the author.

In light of above, the probability of bankruptcy can be presented as follows:

(5) $$p(Y = 1|X) = \frac{1}{1+e^{-L}}$$

$$L = 0.876 - 0.221\,\frac{EBIT}{Total\ assets} - 0.733\,\frac{Cash}{Current\ liabilities} - 1.158\,\frac{Shareholders'\ equity}{Total\ assets}$$

On the basis of tables 6 and 7, the following conclusions on the relationship between the variables and the probability of bankruptcy can be drawn:

1) if the return on total assets (EBITTA) increases by one unit, the probability of bankruptcy decreases *ceteris paribus* 80.2% on the average;
2) if the cash ratio (CASHR) increases by one unit, the probability of bankruptcy decreases *ceteris paribus* 48% on the average;
3) if the equity ratio (EQRATIO) increases by one unit, the probability of bankruptcy decreases *ceteris paribus* 31.4% on the average.

It can be concluded that construction companies that are more profitable relative to their total assets, have a higher ability to meet their short-term commitments and have a higher shareholders' equity relative to their total assets are less vulnerable to bankruptcy.

The cash ratio (CASHR) which only includes the most liquid short-term assets of a company and ignores inventory and accounts receivable, is a liquidity measurement seldom used in bankruptcy prediction models. This can be explained with the fact that in many industries it is not necessary to maintain a high level of cash assets to meet the company's current liabilities. As using WCTA as a liquidity measurement did not improve the predictive ability of the composed model, yet the classification accuracy increased when including CASHR, it can be concluded that the probability of bankruptcy of construction companies is determined by the cash reserves, rather.

The construction sector can be characterized as a specific type of project-based industry where production is unique and the production process is relatively longer compared to other industries. Such peculiarity affects the liquidity of construction companies because majority of the project costs are covered after completing relevant construction work. Terms of payments in the construction sector are relatively longer compared to other sectors and late payments are inherent to the construction sector which is amplified even more due to the seasonality of construction works. Cash reserves can be strongly affected if a main client of a construction company fails to meet its financial commitments; however, at the same time the construction company has to meet its liabilities to subcontractors and other parties in the supply chain. This demands that construction companies hold relatively higher amounts of cash assets to cover their current liabilities. Different from WCTA which includes all current assets, CASHR ignores the inventory and accounts receivable, and thus, enables one to consider the structure of the current assets as there is no assurance that inventory and accounts receivable can be sufficiently quickly converted into cash to duly meet current liabilities.

At the same time, difficulties with liquidity decrease the ability to invest in tangible fixed assets, e.g. machinery and equipment. As presented in descriptive statistics (see table 5) and concluded previously, construction companies that invest less and are focused on less fixed asset-intensive construction works tend to be more vulnerable to bankruptcy. As a consequence, low fixed asset-intensity may lead to lower profitability (lower EBITTA). To compensate the difficulties with liquidity and duly meet current liabilities, companies are searching for different possibilities of financing; this can be complicated due to low measurements of liquidity and profitability ratios. Thus, access to traditional ways of financing, e.g. bank lending, can be relatively limited or the companies have to face higher loan interests, decreasing profitability measurements in general. Using additional financing means that the company finances relatively higher proportions of its assets with debt, resulting in lower equity ratio (EQRATIO). In light of above it can be concluded that profitability, liquidity and leverage categories indicate financial standing as a composite unit, wherein all single components are affected mutually.

The classification accuracy of the models, applied on the same estimation sample, is presented in table 8. Application of the Z``-score LR model (Altman *et al*. 2016) indicates that including an industry specific dummy variable will increase classification accuracy.

Table 8. Classification accuracy of the models on the estimation sample

	Composed model	**Z-score`` LR-model I**	**Z-score`` LR-model II**	**Holdt (2015)**
Non-failed	62.7%	81.3%	62%	99.8%
Failed	74.0%	44.2%	63.6%	11.7%
Overall	68.4%	62.7%	62.8%	55.8%

Source: compiled by the author. Z-score`` LR-model I is without a dummy variable for the construction industry and Z-score`` LR-model II includes a dummy variable for the construction industry.

Z``-score LR model I which is applied without a dummy variable for the construction sector, classifies correctly 44.2% of bankrupt companies. Z``-score LR model II which includes a dummy variable for the construction sector, classifies correctly 63.6% of bankrupt companies. However, the model composed in this study shows higher predictive ability in the group of bankrupt companies (74.0%) as well as higher overall classification accuracy (68.4%) compared to other models assessed in the study.

Holdt's (2015) model based on Estonian construction industry presents poor results and is not widely usable to predict bankruptcy – it classified correctly only 11.7% of bankrupt companies. Such result can be explained with the fact that in this model, the operating companies were selected based on net sales in receding order which indicates that the sample is strongly influenced by the financial data of non-failed companies. Moreover, when a failure prediction model is based on non-random samples, the accuracy results of the model cannot be generalized (Piesse, Wood 1992).

To examine the predictive ability of the model, two types of classification error are distinguished. Type I error indicates the proportion of bankruptcy firms classified as healthy, while type II error indicates the proportion of healthy firms classified as bankrupt (Zhou, Elhag 2007: 304). Previous studies stress that type I error is most likely 15 times more expensive than type II error (*Ibid.*). Type I error usually entails the losses for creditors, whilst type II error includes costs of higher interests and lost profit. Table 8 shows that classification accuracy is the highest in the model composed in this study and, consequently, in this model type I error proportion is the lowest.

The results of applying the composed model on the validation sample are presented in table 9. To strengthen the reliability of results, the Z``-score LR model (Altman *et al.* 2016) which includes a dummy variable for the construction sector, was applied on the same validation sample.

Table 9. Classification accuracy of the models on estimation and validation sample

	Composed model		**Z-score`` LR-model II**	
	Estimation sample	**Validation sample**	**Estimation sample**	**Validation sample**
Non-failed	62.7%	52.1%	62.0%	50.4%
Failed	74.0%	98.2%	63.6%	98.2%
Overall	68.4%	75.1%	62.8%	74.3%

Source: compiled by the author.

Using validation sample indicates that classification accuracy of the composed model in the group of bankrupt companies is 98.2%. Higher classification accuracy on the validation sample compared to the accuracy on estimation sample offers evidence of the goodness of the composed model and shows that financial ratios included in the composed model have high predictive ability outside of the sample. It is noteworthy that the classification accuracy of the composed model and Altman's *et al*. (2016) LR model which includes a dummy variable for the construction sector is similar on the estimation sample as well as on the validation sample, which strengthens the reliability of the results.

5. Conclusion

In this study a bankruptcy prediction model in the example of Estonian construction companies was composed. The Independent Sample T-test showed that the bankrupt companies have lower profitability, liquidity and leverage ratios and that there is a statistically significant difference in the values of financial ratios between bankrupt and operating companies. On the basis of the T-test results, a new three-variable model was composed. Overall classification accuracy of the composed model is 68.4% and it classified correctly 74% of bankrupt companies one year prior to bankruptcy.

Analysis showed that the financial health of companies and the probability of bankruptcy are determined by the set of variables related to the profitability, liquidity and leverage categories. The probability of bankruptcy decreases if the return on total assets, the cash ratio and equity ratio increase. This indicates that construction companies that are more profitable relative to their total assets, have a higher ability to meet their short-term commitments and have a higher shareholders' equity relative to their total assets are less vulnerable to bankruptcy.

Additionally, the Z"-score logistic regression models (Altman *et al*. 2016) with and without a dummy variable for the construction sector as well as Holdt's (2015) model based on Estonian construction industry were applied on the same sample as used in this study. The overall classification accuracy of the Z"-score LR model which includes a dummy variable for the construction sector is 62.8% and it classified correctly 63.6% of bankrupt companies. Holdt's model presented poor results and is not widely usable to predict bankruptcy. The model composed in this study shows higher predictive ability in the group of bankrupt companies (74.0%) as well as higher overall classification accuracy (68.4%) compared to other models assessed in the study.

The results of the study are applicable in practice. The management and shareholders, banks and auditors can evaluate a company's financial standing on the basis of the prediction model and take actions to reduce or avoid possible negative consequences.

Further research could focus on extending the model. Companies with low performance often are witnessing the tax arrears, referring to the company's inability to meet its financial obligations and indicating potential cash-flow insolvency. Therefore, it is a challenging task to analyze whether tax arrears are an indication of temporary financial standing or impending permanent insolvency and whether tax arrears could predict bankruptcy separately or as combined with financial ratios.

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