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BANKRUPTCY PREDICTION OF ROAD TRANSPORTATION FIRMS: EVIDENCE FROM EUROPE

Master's thesis

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Tartu 2018

Name and signature of supervisor: ....

Allowed for defence on ....
(date)

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

The purpose of this paper is to create a bankruptcy prediction model to be able to distinguish between bankrupt and non-bankrupt companies in the road transportation sector in Europe. The analysis is conducted using a logistic regression analysis and financial ratios with good predictive ability from previous bankruptcy prediction studies. The resulting model shows 70.9% accuracy on the test sample one year prior to bankruptcy and a 76.3% accuracy on the control sample. The accuracy of the model exceeds previous multisector models that have also covered the transportation sector, while no models have been specifically composed for this sector.

Keywords: bankruptcy prediction, logistic regression, transportation sector, financial ratios

1. Introduction

Bankruptcies often end with negative consequences. Besides affecting the owners and creditors of the company, it can have a negative effect on the employees, society and the state (Alaka *et al.* 2015, Burksaitiene and Mazintiene 2011). Furthermore, it could also have a domino effect on an entire industry (Jackson and Wood 2013). Therefore, bankruptcy has always been an interesting research topic with practical implications.

Understanding why, how and when companies fail can help many different counterparts: banks in analysing credit risk in a loan portfolio (Hol 2007:76) and institutional and private investors when making better-informed investments and loan decisions (Dimitras *et al.* 1996: 488). Bankruptcy prediction models can signal upcoming potential financial distress that could help decision-makers adjust their strategy (Keasey and Watson 1991: 89-90). Larger companies do not fail overnight and the process that leads to bankruptcy might develop over a long period (Hambrick and D'Aveni 1988). However, since small and medium sized enterprises might go bankrupt faster, their financial statements might not reflect any potential future risks (Lukason *et al.* 2016). It is plausible to observe the decline of some indicators ahead of time, and this may give the management time to adjust strategy and spare the firm from unnecessary distress. To be able to analyse the financial situation, interested parties can use different bankruptcy prediction models.

Altman (1968) was the first to develop a multivariate prediction model in the 1960s. From there it spread all over the world as a tool used by researchers, bankers, investors, asset managers, and even the companies themselves. Altman's bankruptcy prediction model based on multiple discriminant analysis (MDA), was called Z-Score. Leaning on Altman's work, Martin (1977) and Ohlson (1980) were the first to base a bankruptcy prediction model on logistical regression.

Although there is already a good selection of studies exploring company failure prediction models (e.g. Altman 1968, Deakin 1972, Ohlson 1980, Laitinen and Suvas 2013, Altman *et al*. 2017), the road transportation sector at the European level has not been researched. Bellovary *et al.* (2007) have found that most bankruptcy prediction models are compiled on a country-specific basis. In addition, earlier papers, which have mostly focused on country specific failure predictions, have yielded contradictory results, where the models from one country do not fit others (Ooghe *et al.* 2009: 61). The idea of a universal model for predicting corporate failure has been researched by Laitinen and Suvas (2013) and Altman *et al.* (2017). Laitinen and Suvas (2013) found that growing international trade and globalization creates the need for a multi-national universal prediction model.

Within the transportation sector, some research has been conducted in the field of airline failures (Gudmundsson 2011, Lu *et al.* 2014), cargo shipping (Lozinskaia *et al.* 2017), railways (Altman 1973) and the logistics sector (Brozyna *et al.* 2016, Pisula 2012), but no research has been done thus far at the European level in the road transportation sector.

The aim of this thesis is to compose a bankruptcy prediction model for European road transportation firms. As transportation companies often operate on an international level and companies from different countries are intra-connected, creating a pan-European model is expedient.

To compose the model, logistic regression analysis will be used. To reach the aim of the thesis, a model will first be created on a test sample and after that validated on a control (hold-out) sample. The data are gathered from the Europe-wide business statement database Amadeus Business Bureau van Dijk. The financial data gathered between the years 2012 and 2016, consists of 30,434 road transportation sector companies.

This thesis has the following structure. The introduction is followed by a literature review, which has been divided into two subsections – firstly, the definition and prediction of bankruptcy; and secondly, an overview of multisector and transport-sector specific models. The data of the empirical study with the methodology will be described in section three. The fourth part will provide the results of the analysis with relevant discussion, and the last part will provide the concluding remarks supplemented by future research directions and practical implications.

2. Literature review

2.1 Bankruptcy prediction

In the literature, failure is a term that is often used to describe bankruptcy or permanent insolvency. There is no finite definition for failure and because of this, the definition of failure can be interpreted differently. Sharma and Mahajan (1980) have said that a failed company in a broader sense is one that does not meet the management's expectations. The definition of corporate failure is usually dependent on the goal of the research (Karels and Prakash 1987: 575). Researchers who focus on bankruptcy prediction have almost unequivocally used court declaration of permanent insolvency (i.e. bankruptcy) as the definition of a failure in a firm (Mellahi and Wilkinson 2004; Balcaen and Ooghe 2006). Due to the fact that failure prediction studies primarily predict bankruptcy (permanent insolvency), this paper will also use the same definition for failure. The content of bankruptcy is the same in every country; however, different countries have different laws on handling failure and insolvency (Laitinen and Suvas 2013, Altman *et al.* 2017).

The academic research that has been done in the field of business failure and bankruptcy prediction is vast. Having its roots in the 1930s, research has been conducted over the years to find the best prediction model (Back *et al.* 1996). First, the univariate approach was conducted by Beaver (1966), but later the multivariate approach involving multiple discriminant analysis (MDA) was used by Altman (1968), Deakin (1976) and Taffler (1982). Continuing on the path of MDA, Meyer and Pifer (1970) published a linear probability model. Later, Ohlson (1980) popularized the use of a logit model and Zmijevski (1984) came up with the probit model, both the latter take into account conditional probability. Since the 1990's, machine learning techniques have grown in popularity, and among the first to explore these was Tam (1992) using neural networks.

Beaver (1966) used the univariate approach with six different ratios by assigning a breaking point to each ratio. He found that the most accurate ratio to predict bankruptcy was the ratio of cash flow and total debt (Beaver 1966). The pioneer in the multivariate approach was Altman (1968), who used the approach on manufacturing companies, and the main idea was to combine different financial ratios into one weighted index. The index, which is known today as the Z-score, tells us whether the company is successful, unsuccessful or in the grey area, in the latter case it is not possible to classify the company under one of the first two categories (Altman 1968). From the initial 20 variables, only five were included in the Z-score (Altman 1968: 593–594).

In addition to proposing prediction models theoretically or composing them using classical statistical analysis methods, it is also possible to create models to predict failure using machine-learning and artificial intelligence. Jackson and Wood (2013) have found that while machine-learning models are used in 24% of studies seeking to predict bankruptcy, they have also noted that most of the studies today are still made using theoretical (14%) and classical statistical (62%) methods. Furthermore, Tian *et al.* (2012) found that machine learning methods, although increasingly applied, have classification problems. Within the statistical models, the most popular are the MDA and logistic regression-based analyses, proportionately 25% and 21% of all studies use these methods, but of the two the logit has less statistical restrictions (Jackson and Wood 2013).

There are two types of classification errors in bankruptcy prediction. Type I is when a bankrupting company is misconstrued as surviving, and type II classifies a surviving company as bankrupting. The share of errors depends on the cut-off point, meaning how many type I and type II errors exist. According to Balcaen and Ooghe (2006: 69), the cost of mistakes needs to be considered, taking into account how much misclassification can be tolerated by the user of the model. Bellovary *et al.* (2007) state that type I errors are found to be more costly, due to the fact that creditors will be left without their investments and earnings. Koh (1992) found that type II errors cannot be taken lightly either because unmade investments, deals, dividends or interest incur an alternative cost. In real life, the exact cost of errors is hard to measure; therefore, the above-mentioned cut-off point is used to minimize both type I and type II errors (Zavgren 1985, Hsieh 1993).

Although Ooghe *et al.* (2009) find that some failure prediction models could be used widely due to their highly predictive performance, at the same time, they explain that accuracy also depends on timing, industry and strategy. Most prediction models are country specific (Bellovary *et al.* 2007, Altman and Narayanan 1997), but since growth in international trade and globalization has created the need for a multi-country bankruptcy prediction model, Laitinen and Suvas (2013) were the first to elaborate a pan-European prediction model based on 30 countries, with an accuracy of 70%.

2.1.1 Univariate analysis of financial ratios

One of the first studies of bankruptcy prediction that was based on financial ratios was done by the Bureau of Business Research (1930). This was done by taking two financial figures and calculating a ratio from them. The study analysed 24 ratios and found 8 to be the most relevant. According to Balcaen and Ooghe (2006), the biggest contribution of the research was the ability to classify companies into two separate groups; that is, failed and non-failed by comparing the means of important ratios.

Beaver (1966) published a corporate failure prediction study by analysing different financial ratios. He was the first to show that financial ratios have predictive value. According to Beaver (1966), a corporation can be viewed as a *reservoir of liquid assets*, that is increased by income and decreased by liabilities (*Ibid.* 79–80). He (*Ibid.* 78) compared 79 failed and 79 non-failed firms that were similar in area of business and assets, by comparing the mean values for 30 separate ratios. The criteria for the ratios was: frequency in previous literature, classification capability in different research projects and capability to express the ratio via cash flow. He used the univariate approach in his statistical analysis. Out of the 30 tested ratios, there are six that were found to be the most useful (*Ibid.* 78–79):

- Cash flow to total debt
- Net income to total assets
- Total debt to total assets
- Working capital to total assets
- Current ratio = current assets to current liabilities
- No-credit (defensive) interval

Each ratio was analysed separately, and by assigning a breaking point to each ratio, he maximized the classification accuracy. He found that the most accurate ratio to predict bankruptcy was the ratio between cash flow and total debt with 90% accuracy one year before failure, and the best accuracy five years before failure (Beaver 1966: 91). The univariate approach has received a lot of criticism, and Beaver (1966) himself also concluded that a single financial ratio is not reliable enough to predict failure.

2.1.2 Multiple discriminant analysis

Altman (1968) based his research on Beaver's (1966) recommendations and created an MDA model, called the Z-score. In MDA, a model is created by using independent characteristics, their corresponding discriminant coefficients and free agents. In this method, the criterion of the co-variable is a linear function.

By analysing 66 US companies, of which equally 33 were distressed and 33 were functional, Altman included five ratios into the model, although initially there were 22. Those five are: working capital/total assets (X_1); retained earnings/total assets (X_2); earnings before interest and taxes/total liabilities (X_3); market value of equity/book value of total liabilities (X_4); sales/total assets (X_5) (Altman 1968):

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$$

In this model, a company with a Z-score above 2.99 is classified as "non-bankrupt," and enterprises with a score below 1.81 are grouped together as "bankrupt." The grey area is between 1.89 and 2.99 due to sensibility for erroneous classification. The classification accuracy was 95% one year before failure and 72% two years before failure. (Altman 1968)

Altman (1983), taking into account feedback from his colleagues, who had raised the issue of only researching public companies with a value of 100 million USD and up, and who had also highlighted that the sales/total assets ratio has extreme differences between industries, came out with Z'-score, which was specified for private non-manufacturing companies. He removed X_5, the ratio between sales and total assets, and also renamed X_4 as book value of equity/book value of total debt. Therefore, the recalculated Z'-score has the following formula (Altman 1983):

$$Z' = 3.25 + 6.56.X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

In comparison to the initial Z-score, the classification is that companies with a score above 2.6 are "non-bankrupt" and companies with a score below 1.1 are grouped as "bankrupt." The grey area is between 1.1 and 2.6. (Altman 1983). Due to the grey-zone in Altman's (1966, 1983) Z-score, Balcaen and Ooghe (2006) found that it is difficult to differentiate between bankrupt and non-bankrupt firms.

2.1.3 Logit analysis

The first to use the logistic regression method to predict corporate bankruptcy, were Martin (1977) and Ohlson (1980). Although there are many different methods, empirically it has been found that the classification specificity is usually similar between different conditional probability models (Laitinen and Kankaanpää 1999).

Examples of these conditional probability models are logit and probit, the difference being that logit assumes a logistical distribution while probit requires a normal cumulative distribution (Balcaen and Ooghe 2006: 68). Empirically, it has been found that financial ratios are rarely distributed normally (Eisenbeis 1977: 896; Barnes 1987: 581; Karels and Prakash 1987: 581) and using different transformations to obtain a normal distribution can have an effect on the interconnection of the variables or their position in the group (Barnes 1987: 451). The logit model allows for the option to incorporate dummy variables, analyse the statistical importance of different variables, and the direction of the impact of the relationship (Ciampi 2015: 1018), that cannot be achieved by machine-learning or other combined methods. However, the logit model is very sensitive to multi-collinearity (Balcaen and Ooghe 2006: 69), and because financial ratios are often correlated (Chen and Shimerda 1981: 53), multi-collinearity needs to be avoided.

The reason this paper uses a logit analysis over the more popular multiple discriminant analysis, is the fact that MDA does not allow the use of binary variables (dummy data) (Ohlson 1980). Furthermore, when using MDA, the need to group failed and non-failed firms according to set criteria (size or industry) tend to be arbitrary (Ohlson 1980, Jardin 2009). The outcome of the logit model is a conditional probability of bankruptcy in a company (Dimitras *et al.* 1996: 504). Additionally, Ohlson (1980) stated that when applying the logit analysis, the result is always a number between 0 and 1, which represents the likeliness of bankruptcy in percentages; he also found that the score from discriminant analysis is not that easily interpreted (Ohlson 1980: 112). Logistic regression analysis mainly has a cut-off point at 0.5 (Laitinen 1999). If bankruptcy is coded as 1 (L=1), that means that companies are classified as bankrupt when the score is over the cut-off point of 0.5, and when the score is under the cut-off point, they are classified as non-bankrupt (L=0). It is important to emphasize that the logit model does not directly predict bankruptcy, but rather gives a statistical evaluation, whether a company's profile is similar to a bankrupt or an active company (Balcaen and Ooghe 2006: 77). The general logit model is as follows (Ooghe *et al.* 2009):

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

$$\text{where } L = b_0 + b_1V_1 + b_2V_2 + \ldots + b_nV_n$$

where L_i – the logit score between 0 and 1, e.g. probability of bankruptcy

V_i – the independent variables of the model

b_i – the coefficients

2.2 Bankruptcy prediction models for the transportation sector

Earlier studies have shown that single sector models do not provide the same classification accuracy on other sectors (Mensah 1984, Chava and Jarrow 2004). The reason for that might be that each sector has its own specific business logic, strategic standpoints and market dynamics (Thornhill and Amit 2003). There are also different competition and risk levels between sectors (Chava and Jarrow 2004). Furthermore, companies at different levels of growth and different markets have a very specific and strategically different approach to doing business (Moulton *et al.* 1996). Chen and Shimerda (1981) found in their research that each business sector has its own specific indicators that need to be taken into account, when predicting failure. Furthermore, Gupta and Huefner (1972) and Gambola and Ketz (1983) have found that the average level of different ratios is different by sectors.

Due to the limited amount of research specific to road transportation, the author has created a comparative table (Table 1) comprising 14 different studies. The first ten are transportation industry analyses that use the logit method, the next two are transportation specific studies that use other methods (Gudmundsson 2011, Altman 1973). Lastly, there are two multi-sector failure analyses that also include the transportation sector (Laitinen and Suvas 2013 and Altman *et al.* 2017). Table 1 serves to give a brief overview of previous research in the sector and to give a point of comparison for this paper's results.

As shown in Table 1, eight out of ten transport and logit articles have collected their data from one specific country and provide an accuracy on the test sample between 52 and 92%. The same eight studies provide a 75 to 92% accuracy on the control sample. The high volatility in the results may be caused by many different factors. One of the key characteristics to point out is that the sample sizes vary greatly – from 60 (Balina and Juszcyk 2014) to 21 840 (Lundqvist and Strand 2013). Additionally, the other two papers that have multi-country data – Lozinskaia *et al.* (2017) and Merikas *et al.* (2015) – provide a classification accuracy of 69% and 71% respectively.

It is important to note that the only article that, as in this paper, has specifically targeted road transportation firms is Balina and Juszcyk (2014). However, due to the small sample (60 firms) and country specific limitations (only companies registered and headquartered in Poland), the resulting 83% and 78% classification accuracy on the test and control sample do not provide a good comparison to the multi-country research with a wider data set.

Laitinen and Suvas (2013) and Altman *et al.* (2017) have researched firms from all sectors excluding the financial sector across 34 countries around the world. Their dataset is vast, reaching over 3.4 and 5.8 million, respectively. The classification accuracy of 70% and 74% on the test sample is a good comparison point for this paper, as both of them use a multi-country approach.

Of all the articles, Vochozka *et al.* (2015) is the only one who has used a non-standard classification of bankruptcy, by classifying bankrupt firms as 0 and non-bankrupt as 1. All the rest of the studies classify bankrupt firms as 1 and non-bankrupt firms as 0.

Table 1. Overview of previous transportation sector bankruptcy prediction studies (compiled by the author)

Author, year	Vochozka 2015	Lozinskaia *et al.* 2017	Brozyna *et al.* 2016	Lu *et al.* 2014	Pisula 2012	Kanapickiene 2016
Sample size, failed / non-failed	12 930, N/A	192, 41/151	66, 33/33	190 firm years, 48/142	225, 61/164	265, 135/130
Sector	transport and shipping	cargo shipping	transport, hauling, logistics	air transportation	logistics sector	transport and storage
Country	Czech Republic	36 countries, listed companies	Poland, Slovakia	USA	Poland	Lithuania
Data years	2003-2012	2001-2016	1997-2003	1990-2011	2004-2012	2007-2012
Method used	logit	logit	logit	logit	logit	logit
Classification accuracy on test sample	92%	69%	92%	52%	85%	82%
Classification accuracy on control sample	92%	N/A	84%	75%	90%	N/A
Classification type	0- bankrupt, 1 non-bankrupt	1- bankrupt, 0 bankrupt	bankrupt 1, non-bankrupt 0	bankrupt 1, non-bankrupt 0	bankrupt 1, non-bankrupt 0	bankrupt 1, non-bankrupt 0
Variables used in the model	0.095064x Constant; 0.0619x Equity; 0.4463x Registered capital; 1.062x Current liabilities; 0.00249x Profit/ loss; 0.5362x Share of receivables on current assets; 0.259x Payment time of payables from trade; 0.09527x Quick test; 0.194857x Working capital index; 0.2053x Capital coefficient of added value; 0.1493796x Long-term liabilities/ liabilities; 0.2132x current liabilities/ liabilities; 0.191x Long-term credits and loans/ liabilities	0.011x TobinQ; 0.001x EBITDA; 0.018x Ln of Total Assets	0.04938x Current assets/ Short term liabilities; 0.11751x Net profit/Net sales income; 0.04283x Fixed assets (without long-term prepayments and accruals)/ Balance sheet total	2.9357x Intercept; 0.39437x Ln(Total assets); 0.58292x Quick assets/ expenditure for operation; 3.9796x Increase in sales prior to year's sales; 4.2801x Working capital/ total assets	0.00458x Current assets / Short-term liabilities; ROA; 0.00638x Net profit/ Net income from sales; Total liabilities / Equity capital; 0.00387x (Equity capital + Long-term liabilities) / Fixed assets; 0.00577x Fixed assets / Current assets	1.226x EBIT/ Total assets; 1.845x (Current liabilities)-Cash)/ Total assets; 1.843x Working capital/ Total assets; 4.141x Total liabilities/ Total assets; 0.09x Equity/ Fixed assets; 0.726x Current assets/ Sales; 0.678x Equity/ Sales; 3.859x Cash/ Total assets; 1.319x Receiveables/ Total assets

Table 1. continued

Author, year	Fedorova *et al.* 2015	Merikas *et al.* 2015	Lundqvist & Strand 2013	Balina 2014	Gudmundsson 2011	Altman 1973	Laitinen & Suvas 2013	Altman *et al.* 2017
Sample size, failed / non-failed	645, 145/500	208	21840, 355/21485	60, 20/40	41, 18/23	21 failed	3.4M / 56 541	5.8M, 81 879/ 5.7M
Sector	transport	shipping	transportation & storage	road transport companies	airlines	railways	industrial companies	non-financial industrial companies
Country	Russia	Internationally listed	Sweden	Poland	worldwide	USA	30 across Europe	31 European countries and USA, China, Colombia
Data years	2010-2013	2000-2014	2006-2011	2007-2010	5-year span	1939-1970	2002-2010	2002-2010
Method used	logit	logit	logit	logit	neural networks	Linear Discriminant analysis	logit	Z" score
Classification accuracy on test sample	85%	71%	77%	83%	82%	98%	71%	74%
Classification accuracy on control sample	N/A	N/A	78%	78%	N/A	83%	71%	74%
Classification type	bankrupt 1, non-bankrupt 0	bankrupt 1, non-bankrupt 0	bankrupt 1, non-bankrupt 0	bankrupt 1, non-bankrupt 0	N/A	N/A	bankrupt 1, non-bankrupt 0	bankrupt 1, non-bankrupt 0
Variables used in the model	0.29x Turnover of circulating assets; 1.45x Short term debt/ Aggregate liabilities; 0.42x Net circulating capital/ Aggregate assets; 8.24x Profitability of assets; ROA; 0.9x Coefficient of autonomy; 1.01x Accounts receivable/ Aggregate assets; 0.94x Working capital/ Assets; 0.06x Log (Physical assets); 0.58x Log(EBIT/ Interests payable); 0.00002x Reverse coefficient of absolute liquidity	0.0083x ROE; 0.0334x Ln (Total assets); 0.0149x OWN(% of stakes held by largest stakeholder)	0.0946x Intercept; 0.0088x Total liabilities/ Total assets; 0.1386x Liquidity/ Total assets; 0.5116 Operating profit+ financial income/ Total assets; 0.0011x Log (Total assets)	1.878x Constant; 3.075x Current assets/ Total assets; 0.02263x Total liabilities/Equity capital; 0.0057x Equity capital/ Fixed assets; 0.003228x (Short term receivables+ short term investments)/ current liabilities	passenger average haul (ratio); departures per aircraft (ratio); average age of fleet (continuous); available seat kilometers per employee (ratio)	0.2003x Cash flow/ Fixed charges; 0.2070x Transportation expenses/ Operating revenues; 0.0059x Earned surplus/Total assets; 0.0647x 3-year growth rate in operating revenue; 0.1040x Earnings after taxes/ Operating revenues; 0.0885x Operating expenses/Operating revenues; 0.0688xEBIT/ Total assets	0.3329x Intercept; 0.1043x ROA; 0.0385x Quick asstes/Total assets; 0.4534x Equity ratio; 0.0313x Total assets; 0.0082x Total assets(2); 0.0794x semi-deviation of ROA	0.035x Constant; 0.495xWorking capital/ Total assets; 0.862xRetained earnings/ Total assets; 1.721x EBIT/ Total assets; 0,017x Book value/ Equity/ Total liabilities

Note: The databases used to find articles, were ebsco.com, emeraldinsight.com, jstor.org, scholar.google.com and sciencedirect.com.

The ten different studies use 46 different variables and only 13 of them appear in more than one study. This illustrates the fact that the areas of research have been very different (oil and cargo shipping; hauling; logistics; air, road and rail transport), and therefore different industry specific variables are being tested. The full overview of all variables on the basis of grouping can be seen in Appendix 1.

Table 2 provides an overview of the main variables in the transportation sector. The categorization of the main variables is based on the work of Lukason *et al.* (2016), where the authors have categorized different variables and compiled a comprehensive differentiation of ratios. The ratios by category are widely used across most studies; therefore, trying to dwell on industry specifics is not reasonable.

Table 2. The main significant variables in bankruptcy prediction models for transportation firms (compiled by the author)

Domain	Variable
Liquidity	Current liabilities/ Liabilities, Current assets/ Short term liabilities, Working capital/ Total assets, (Current liabilities-cash)/ Total assets, Receivables/ Current asset
Productivity / Activity	Equity/ Sales, Current assets/ Total sales,
Profitability	Earnings before interest and taxes/ Total assets, Net profit/ Net sales, Return on Assets
Solvency / Financial structure	Total liabilities/ Equity, (Equity capital + Long-term liabilities)/ Fixed assets, Ln of Total assets (LnTA)

Note: Each significant variable in at least two models from Table 1. LnTA is solvent because it shows long-term financial capability.

3. Data and methodology

Taking into account the previous chapter's findings based on prior research and also in order to avoid multicollinearity, this study uses the following independent variables (followed by abbreviation of ratio in brackets):

- [Current assets- Current liabilities] / Total assets (WCTA),
- Earnings before interest / Total assets (EBITTA),
- Total equity / Total assets (TETA),
- Operational revenue / Total assets (OPRTA).

In addition to the arguments above, using these four variables is already theoretically motivated by Altman *et al.* (2017) and Altman (1968). The variables of total equity over total debt and retained earnings over total assets used in Altman *et al.* (2017), were not added to this paper due to their multicollinearity and similarity to TETA. In addition, the chosen variables cover the areas of liquidity, productivity, profitability and capital structure, which were found to be relevant by Balcaen and Ooghe (2006). Since the Amadeus database only gives the data from financial statements, the cash flow based variables are not included in this study.

According to the European Commission (2017), in 2014 the EU had around 550 000 road haulage companies, and of them, almost half were from Spain (103 000), Poland (79 000) and Italy (69 000). All three are also included in the data set for this research paper. Furthermore, the sector employed around three million people and generated a turnover around 330 billion in 2014 (European Commission 2017).

Research and Markets (2017) have concluded that in terms of revenue about two thirds of the European road freight market consists of companies with less than 50 employees. In addition, 54% of EU road freighters have only one employee and in total 90% of companies in the sector have less than ten employees. Furthermore, most truck operators are small firms with less than 10 vehicles in operation. This is due to the fact that big companies hire sub-contractors to work assets flexibly and avoid tying up company finances in assets such as trucks. The road freight market is quite predictable and the low volume growth figures (single digit growth year-over-year) correlate with fluctuations in the economy. Also, companies that are in Central and Eastern Europe account for around 60% of traffic, while Poland is the single biggest hauler with 30% of traffic. (Research and Markets 2017)

Data necessary for this quantitative research is taken from the database of Bureau van Dijk's (BvD) Amadeus. The database combines all European credit databases into one single system and provides that data publicly for research purposes. This paper brings together companies that have gone bankrupt between 2012 and 2016. Using the Statistical Classification of Economic Activities in the European Community (NACE) 2008, the data for this research is compiled using companies who are in the category *Freight transport by road and removal services* (NACE 494).

The data set consists of bankrupt and non-bankrupt companies. Firstly, a data set of 30,434 bankrupt companies were downloaded from the database. Some countries do not have the status "bankrupt," instead they use "active (insolvency proceedings)" when a company starts bankruptcy proceedings, and later, when the company is bankrupt, the status of the company is "in liquidation." Therefore, companies with the status "bankrupt" or "in liquidation" were included in the data set if the latter also previously had the status "active (insolvency proceedings)." The companies included in the sample also had to have filed their financial statements for the period 2012–2016. If they had the necessary data to calculate the relevant variables, they were included in the data set. After all the filters were applied, the final sample consisted of 4,031 bankrupt companies. After downloading the list of active companies and filtering out all the firms that had the necessary data, there were 11,747 non-bankrupt companies, making the total dataset 15,778. Since the data will be weighted later on, the number of bankrupt and non-bankrupt companies does not need to be equal. An active company in this study refers to a company that is operating, has no ongoing or finalized bankruptcy proceedings and is financially active. The average Total Assets (TA) for the companies in the data set was around 822,000€.

Eighty per cent (80%) of the companies in the data set were selected at random to create the test sample, and the remaining 20% were later used as a control group to test the formula. The breakdown of the dataset is provided in Table 3.

Taking into consideration the characteristics of this study, the analysis method applied is a logistic regression analysis (LRA). As mentioned before, LRA is one of the most widely used in the literature, works better on large samples (Altman *et al.* 2017), and according to Balcaen and Ooghe (2006), using a cut-off point makes a very clear distinction between bankrupt and non-bankrupt firms.

Table 3. Bankrupt and active companies by country (compiled by the author)

Country	Test data		Control data	
	Bankrupt firms	**Non-bankrupt firms**	**Bankrupt firms**	**Non-bankrupt firms**
Belgium	218	525	61	86
Spain	79	1552	17	358
France	1567	1450	383	389
Hungary	188	1440	46	331
Italy	546	1489	136	387
Poland	184	1511	38	401
Portugal	453	1427	115	401
Total	3235	9394	796	2353

Since companies who are going bankrupt tend to not file their financial statements one year prior to bankruptcy, previous studies have tackled this issue in two different ways. The easiest way is to take the latest filed statements, as Beaver (1966), Altman (1968) and Ohlson (1980) have all done. However, the filing of the statements might be too close or too far from the bankruptcy, so it might not provide the correct data. Dimitras *et al.* (1996) and Bellovary *et al.* (2007) have found that using earlier data, not just the most recent before bankruptcy, increases the available data significantly because the closer companies are to bankruptcy, the less they submit their financial statements. This paper uses both approaches by using the most recent financial statements. The reports cannot be too close to the moment of failure and also the oldest financial statement should be no more than two years old. If a company went bankrupt within the first half of the fiscal year, the statements from two years before were used, when a company went bankrupt in the second half of the fiscal year, the financial statements of one year before were used. All the older data was discarded from the dataset.

The linear regression will be calculated as a uniform model based on the test data, and the formula will then be tested on the control group, while also providing country-specific results for comparison. The dependent variable Y=0 will be used for non-bankrupt firms and Y=1 will be used for bankrupt firms. In this research, the cut-off value for the dependent variable is 0.5, meaning that a result below 0.5 will be classified as non-bankrupt and a result above 0.5 will be classified as bankrupt.

It is safe to assume, that bankrupt and non-bankrupt companies affect the probability of bankruptcy equally. However, the test and control group data do not have exactly the same amount of observations; therefore, weights are applied to remove the discrepancy. The formula to calculate the weighting factor (W) is:

$$W = 0.5 \div proportion\ of\ the\ observations\ in\ the\ total\ data\ set$$

The proportion of the observations for bankrupt companies is calculated by dividing the total number of bankrupt firms by the total number of bankrupt and non-bankrupt companies. In the same manner, the proportion is calculated for non-bankrupt companies, where the amount of non-bankrupt firms is divided by the total amount of companies. Thereafter, W is found by dividing 0.5 with the right proportion of observations. This is congruent with previous studies, such as Laitinen and Suvas (2013) and Lozinskaia *et al.* (2017). The statistical analysis was carried out using the statistics software *IBM SPSS Statistics.*

4. Results and discussion

Using the results from the whole data set of both bankrupt and non-bankrupt firms, the descriptive statistics of this study are presented in Table 4 below, where N stands for the number of examples in the data set, and the median, mean and standard deviation have also been provided.

As Table 4 shows, the median and mean scores for non-bankrupt companies are close to each other for the variables WCTA, EBITTA and TETA, which indicates symmetry of distribution. However, the mean scores for the aforementioned three ratios for bankrupt firms exceed the median scores, which shows a negatively skewed distribution. In the case of variable OPRTA, the median exceeds the mean by a significant margin in both bankrupt and non-bankrupt firms, which indicates a positively skewed distribution.

Table 4. Descriptive statistics for each of the independent variables in this study

Failure		**WCTA**	**EBITTA**	**TETA**	**OPRTA**
Non-bankrupt	N	9 394	9 394	9 394	9 394
	Median	0.16	0.05	0.31	1.85
	Mean	0.15	0.07	0.31	2.07
	Std Deviation	0.35	0.17	0.35	1.05
Bankrupt	N	3 235	3 235	3 235	3 235
	Median	-0.07	-0.01	0.05	1.94
	Mean	-0.32	-0,15	-0.26	2.10
	Std Deviation	0.84	0.58	0.89	1.45
Total	N	12 629	12 629	12 629	12 629
	Median	0.11	0.04	0.24	1.87
	Mean	0.03	0.01	0.17	2.07
	Std Deviation	0.56	0.34	0.60	1.16

Source: compiled by the author

Table 5 presents an overview of the model variables and their predictive abilities. As the table shows, WCTA, reflecting firm liquidity, is insignificant, and therefore the level of liquidity does not differ between bankrupt and surviving firms. This is a key finding from this research, because Lu *et al.* (2014) and Kanapickiene (2016) found liquidity to be significant. The productivity, profitability and capital structure of the rest of the variables show that the more revenue a firm earns on the basis of its assets, the more profitable it is, the greater its equity levels, and the less likely it is to go bankrupt.

Table 5. Variables in the model

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
WCTA	0.126	0.084	2.257	1	0.133	1.134
EBITTA	-1.143	0.107	114.922	1	0.000	0.319
TETA	-2.361	0.096	610.592	1	0.000	0.094
OPRTA	-0.097	0.017	31.695	1	0.000	0.907
Constant	0.538	0.045	141.364	1	0.000	1.712

Source: compiled by the author

Table 6 shows the Cox, Snell and Nagelkerke R Square indicators, which show how well the model fits the data.

Table 6 The goodness of fit of the model (compiled by the author)

Indicator	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Goodness of fit value	14447.798	0.215	0.287

The bankruptcy prediction formula found in this thesis, is represented as follows:

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

where L= 0.5378 + 0.126*WCTA – 1.1429*EBITTA – 2.361*TETA – 0.0975*OPRTA

When running the LRA model on SPSS, after applying W, the test sample included 6,315 bankrupt and 6,314 non-bankrupt firms. The accuracy of the model’s classification on the test sample was 77.5% for non-bankrupt firms and 64.3% for bankrupt firms. The overall accuracy for predicting bankruptcy on the test sample was 70.9%.

When using the resulting formula on the control group, the results were significantly better for the whole model. The predictive accuracy on the control sample was 79.9% for non-bankrupt firms and 65.5% for bankrupt firms. The total accuracy of the model on the control sample was 76.3%. Table 7 shows the results of the test sample by country. The fact that the classification accuracy is lower when implementing the model on the test sample and higher on the control sample shows the goodness of the model.

Table 7. Classification accuracy on the control sample by country

	Classification accuracy (%)		
Country	**Non-bankrupt**	**Bankrupt**	**Total**
Belgium	79.07	57.38	70.07
Spain	81.28	82.35	81.33
France	91.26	53.26	72.41
Hungary	90.03	67.39	87.27
Italy	57.88	89.71	66.16
Poland	88.78	57.89	86.10
Portugal	72.32	80.87	74.22
all countries	79.98	65.45	**76.31**

Source: compiled by the author

The prediction accuracy of 70.9% on the test sample and the 76.3% on the control sample compare well with the average result of other studies presented in Table 1. This result is close to that of Lozinskaia *et al.* (2017) and Merikas *et al.* (2015), who found a classification accuracy of 69% and 71% respectively. Both of these studies created their transportation specific model on an international basis.

The highest predictive accuracy for the model is for Hungary, with 87.3% accuracy. By comparison, Altman *et al.* (2017) yielded a result of 74.2% for Hungary. Laitinen and Suvas (2013) received a result of 71.9% and Altman *et al.* (2017) a 77.2% classification accuracy for Belgium, whereas this study's finding is 70.1%.

For Poland, which is one of the largest road hauling countries in the EU in terms of traffic and number of hauling companies (European Commission 2017), the current model accurately classified 86.1% of cases. Balina and Juszcyk (2014) and Pisula (2012) both focused their study on the Polish market and their model accuracy was 83% and 85% on the test sample respectively and 78% and 90% on the control sample. It is important to note that Pisula (2012) used one and Balina and Juszcyk (2014) used two more variables in their model. Additionally, Laitinen and Suvas (2013) achieved an accuracy of 83.3% for Poland.

The third best result in this model is for Spain, with 81.3% accuracy. Altman *et al.* (2017) achieved 73.4% accuracy for Spain, and Laitinen and Suvas (2013) predicted correctly 70.1% of the time with their model. According to the European Commission (2017), Spain is the home of nearly 19% of all the road hauling companies in Europe.

Two tests were run to analyse and compare the research results. Firstly, the model from Altman *et al.* (2017) was applied to the same dataset for which the necessary variable information was known. The total data sample is slightly smaller for the model by Altman *et al.* (2017), due to the fact that some data for the variables were not available. The appropriate data is provided in Table 8. As can be seen from Table 8, the model by Altman *et al.* (2017) classifies non-bankrupt companies correctly 13.6% (1597/11700) and bankrupt companies correctly 45.7% of the time (1840/4024). The weighted average accuracy of the model is 29.65%. The result from the model by Altman *et al.* (2017) is roughly 2.5 times less accurate than the LRA model created in this research, making the result of this study far superior as a pan-European multi-sectoral model.

Table 8. Performance of the model by Altman *et al.* (2017) using data from this study

		Predicted		**Total**
		0	1	
Actual Status	0	1597	10103	11700
	1	2184	1840	4024
Total		3781	11943	15724

Source: compiled by the author

Secondly, neural networks were used to test whether the accuracy of the results could be improved. The overall accuracy of the model rose to 81.7% on the training model, 82.1% on the test model and 82.6% on the holdout sample. It is important to keep in mind that the data is not weighted, and the goal for the program is to classify the surviving companies as highly as possible. Applying a weight to this data in neural networks would not improve the results, keeping them in the same area or even below this paper's result.

5. Conclusions

The objective of this study was to provide a universal failure prediction model for use in the road transportation industry. The paper analysed 15,778 companies from seven different European countries, where a random set of 80% of companies were used to create the model, and 20% were used as a control to test the model. The variables were chosen based on previous literature to indicate the most used prediction variables.

The overall accuracy of the created model was 70.9% on the test data and 76.3% on the control data. This is better than previous multi-country studies which have included the transportation sector, such as Laitinen and Suvas (2013), whose model's accuracy was 70% both on the test and control data, and Altman *et al.* (2016), with the model showing 74% accuracy also on both the test and control data.

This study has identified three ratios that have high predictive capability in the model – Earnings Before Interest / Total Assets (EBITTA), Total Equity / Total Assets (TETA) and Operational Revenue / Total Assets (OPRTA). Working capital / Total Assets (WCTA), the firm liquidity ratio, was found to be insignificant, meaning that liquidity does not differ between bankrupt and non-bankrupt firms. The accuracy of the model is average, being higher in some countries (Poland, Hungary and Spain), and low in predictive capability in others (Italy, France, Belgium).

This holds two practical implications: firstly, future research can take the findings of this thesis into account when selecting variables, and secondly, the countries where the composed model works well are now known. Furthermore, adding non-financial variables could improve the accuracy of the model, as shown by the example of Poland, where Pisula (2012) achieved an accuracy of 90%.

The literature review provided many region and country specific models that used more variables than the four used in the model in this study. By applying region specific modifications to the model or creating new models with country specific variables, one could provide greater accuracy in the final outcome of the model.

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Appendix 1. Categorized variables used by previous articles, bold indicates the use in multiple models (compiled by the author)

Liquidity	Productivity	Profitability	Activity	Solvency	Financial structure
Receiveables/ Current assets	**Current Assets/ Total sales**	**EBIT/ Total assets**	**Equity/ Sales**	**Ln of Total Assets**	**Total liabilities/ Equity**
(Current liabilities-cash)/ Total assets	(Short term receivables+ Short term investments)/ Current liabilities	**Net profit/ Net sales**	Cash/Total Assets	Total market value/ Total assets (TobinQ)	**(Equity capital + Long-term liabilities)/ Fixed assets**
Working capital/ Total assets	(Operations profit+ Financial income)/Total assets	**Return on Assets**	Increase in sales prior to year's sales	Financial Expenses/ Total assets	Equity
Current assets/ Short term liabilities		Capital coefficient of added value			Fixed assets / Current assets
Current liabilities/ Liabilities		Return on Equity			Total liabilities/Total assets
Long term credits and loans/ Liabilities		Logarithm (EBIT/interests payable)			Equity/ Fixed assets
Payment time of payable from trade		Profit/Loss			Logarithm of physical assets
Quick assets/ Expenditure for operation		EBITDA			% of stakes held by largest stakeholder (OWN)
Current assets/ Total assets					Registered capital
Reverse coefficient of absolute liquidity					Fixed assets (without long-term prepayments and accruals)/ Balance sheet total
Liquidity/ Total assets					
Logarithm of Total assets					
Current liabilities					
Total assets					
Working capital					
Long term liabilities/liabilities					

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