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FAILURE PREDICTION OF YOUNG MANUFACTURING FIRMS: EVIDENCE FROM EUROPEAN COUNTRIES

Master's thesis

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Tartu 2021

We have written this Master Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

Abstract

Although prediction of failure is a well published issue, there are not so many publications for young manufacturing companies and there is no international comparison. The aim of the thesis is to create a model of failure prediction for young European manufacturing companies. The analysis used the financial data of 56,822 public and private companies (3,987 failed and 52,835 non-failed). All the young European manufacturing companies that have been established since 2013 were used. Logistical regression (LR) with 9 financial variables was used to compile prediction models. In general, all variables used in this thesis show mediocre accuracy, none exceeding 70% and there are significant differences in accuracy between countries due to country-specific financial data. This shows that profitability variables have the greatest impact on the successful sustainability of a company.

Keywords for articles: newly founded firms, manufacturing industry, business failure, logistic regression, insolvency, young manufacturing firms.

CERS: S180, S181, S190, S192

Introduction

It is important for every starting entrepreneur to know more about the risks that can be avoided even before starting a business, and what economists can teach students and publish for all interested people to read. The ability to identify or judge firms headed for failure is always important for stakeholders, and particularly in times of economic crisis (Wu, 2010).

Moreover, this study may also benefit investors and bankers. It is beneficial for them, because they can assess where to invest and whether it would be useful to buy a company or its shares. In his empirical study, Laitinen (1992) states that there is a correlation between the capital of the initial stockholders and the total capital, which confirms that the initial investment in starting a business has a major impact – the higher the shareholding when starting a company, the greater the probability of success. However, it is very different from country to country how much capital must be invested when starting a business and these companies are affected differently by the local tax system and the market. Predicting business failure is a difficult process because it is necessary to take into account the different aspects of business and economic environment as accurately as possible (Mackevičius, 2018).

The aim of the thesis is to create a model for predicting the failure of young European manufacturing companies. This involves analysing the predictability of financial desperation of European manufacturing firms and then comparing them with a selection of similar previous articles. The major finding was that profitability variables lead to the most accurate results in predicting failure. The Amadeus database was used in this thesis. If we look at all European companies in this database, for example for 2015, we see that there are about 25 million companies (all kinds of old and young companies, manufacturing and service companies, etc.) and from this report we can see that many companies have already closed down within 5 years and in a practical sense such a study is important to understand the failure and success rates for those who want to start their own new companies for example.

Our initial sample of companies consisted of 35,056 failed and 75,070 non-failed companies, which after filtering was reduced to 3,987 failed and 52,835 non-failed companies. The second criterion used to identify failed firms was that they had gone bankrupt or been declared insolvent within 5 years. The criterion of 5 years was also used for the non-failed companies, as all enterprises used in the analysis had to have been active for more than 5 years.

Logistic regression was chosen as the statistical method for this study in order to build failure prediction models. We have produced two tables illustrating the results using 9 variables and 9 countries as well as an overall analysis of 35 countries. The aim is to show the specific variables that provide the highest and lowest accuracy and an overall analysis showing which countries have higher and which have lower accuracy in predicting failure.

In this thesis, we review the literature focusing on failure prediction, logit regression and different variables. The chapter on data and methods provides a clear overview of the methods used. This is followed by the results and discussion and the conclusion of the thesis.

1. Literature review

In reviewing various articles on failure prediction, we came to the realisation that each researcher defines failure differently and that there are no universal techniques and methods Pretorius (2009). The authors aim to provide insight not only to the manufacturing industry but also to interested readers by showing different kinds of comparison between different methods, different regions and different techniques. We reviewed and collected data from the literature and used all relevant data in our tables (Table 1 and Table 2). In this thesis, based on the literature review, two tables were constructed based on different types of studies that have been done in this field. The first table provides a more general overview of the selected failure prediction studies, more specifically the focus of the articles, methods, sample size, region, sector and period. This is simply to see how the authors of the articles approach business failure prediction, using different strategies and trying to create more effective methods. This topic has been studied for several years, but little use has been made of the results. In order to avoid business failure and the resulting damage, different methods for predicting business failure are presented in Wu (2010). It can be seen from the articles on business failure prediction that even these focus on different methods, but logistic regression is the most common, so we have compiled a second table based only on those articles that have used logistic regression. In this table we have selected eleven articles and the table shows the variables applied, the variables in models and accuracy information as columns.

Forecasting and studying bankruptcy has been of considerable interest to accountants, practitioners and economists over the past four decades Kim & Partington (2008). All the articles used in this study were searched in databases using the keywords: newly founded firms, manufacturing industry, business failure, logistic regression, insolvency and young manufacturing firms. From the articles found using these keywords, the relevant were selected for use and have been cited in the thesis. Table 1 presents data based on previous literature mainly on European and manufacturing firms, as this was the focus of this thesis, but we also included some articles from outside Europe - Colombia, USA, Japan, Malaysia and Turkey. Articles by authors from these countries were included to add diversity and depth to the analysis as a comparison with companies outside Europe. This demonstrates the global relevance of research into failure prediction. The sample size for building prediction models varies widely with the Altman et al. (2017) article being the largest - over 2,600,000. All the methods used are indicated by abbreviations in the table and their exact name is given in the legend. In both tables, articles were also included that did not only use prediction methods, but included information, comparing different methods, comparing prediction models, or just comparing innovativeness.

The present study reviewed articles on active and inactive firms from 1968 to 2020, and as we can see, failure prediction has been a topic of interest for researchers for a long time, and it continues to be of interest today. Most of the articles date back to the 21st century, but the oldest is from 1968 and was the first study to use different ratios in the models at the same time and the first to use Multiple Discriminant Analysis (MDA). Aziz (2004) examined the different methods based on Altman's (1968) article and found that due to Altman's (1968) study, MDA has been used extensively since then.

As mentioned, the articles are mostly from the 21st century, and most of them from 2014-2018, but one of the most important recent studies is the study by Fuertes-Callen et al. (2020) on predicting the survival of Spanish start-ups.

In this thesis, four studies have been selected in which Erkki K. Laitinen has been the researcher, either individually or as a co-researcher. He is the author of one of the most important articles in the field - his study from 1992 was a pioneering one in the world, as it was the first study on the prediction of failure of small young enterprises. The main aim of this study was to find methods for predicting failure, especially for small firms (Laitinen, 1992). It found that a low first stockholders' capital to total capital ratio is a high risk for a young firm and that multivariate analysis can be more accurate than univariate analysis, although not overwhelmingly so (Laitinen, 1992).

Table 1

Selection of articles focusing on failure prediction: article focus, methods, sample size, region, target group, period (composed by authors).

Article	Article focus	Methods (*)	Sample Size	Region	Target Group	Period
Fuertes-Callen et al. (2020)	Prediction	T, M, LR	6167	Spain	New-born SUs	2007-2015
Hosaka (2019)	Prediction	MLM	2062/7520	Japan	Continuing/Bankrupt firms	2002-2016
Munoz-Izquierdo et al. (2019)	Prediction	LR	808	Spain	Failed firms	2004-2014
Abdullah et al. (2019)	Prediction	LR	732	Malaysia	Manufacturing	2000-2010
Arroyave (2018)	Prediction	LR, MLM, DA	3	Columbia	Energy Sector	2008-2015
Tong & Saladrigues (2018)	Prediction	LR	17247	Spain	Manufacturing, Logistics	2009-2014
Altman et al. (2017)	Prediction	LR	2602563 non-failed; 38215 failed firms.	31 European, 3 non-European countries	Industrial	2002-2010
Ciampi (2017)	Prediction	DA	3200	Italy	Manufacturing	2012-2016
Lukason & Käsper (2017)	Prediction	LR, FCA	417	Estonia	Goverment Funded Sus	2004-2013
Lukason et al. (2016)	Failure Processes	FCA	1216	11 European countries	Manufacturing	2005-2015
Lukason & Laitinen (2016)	Prediction	LR	1235	15 European Countries	Old Manufacturing	-
Ciampi (2015)	Prediction	LR	3210	Italy	SMEs (manufacturing, building, services)	2008-2010
Odibi et al. (2015)	Prediction	LR, LiR	34	Malaysia	Manufacturing	2010-2014
Laitinen et al. (2014)	Prediction	T	>600	US, UK, Belgium, Czechia, Croatia, Estonia	Not specified	1992-2012
Laitinen & Suvas (2013)	Prediction	LR	1000000 active, >20000 failed	30 European countries	Industrial	2002-2010
Wu (2010)	Comparison of previous techniques	-	-	-	-	-

Donker et al. (2009)	Prediction	LR	177	Netherlands	Amsterdam stock trading companies	1992-2002
Vuran (2009)	Prediction	DA, LR	122	Turkey	Publicly opened and closed firms	1999-2007
Wetter & Wennberg (2009)	Prediction	LR	1735	Sweden	-	1995-2002
Alfaro et al. (2008)	Prediction	MLM	1180	Spain	Failed firms	2000-2003
Veugelers (2008)	Innovativeness compared with SMEs and Large Firms	-	-	European Countries	SMEs and Large Firms	2002-2008
Balcaen & Ooghe (2006)	LR, M, DA comparison	-	-	-	-	-
Gepp (2005)	SA and DT / Compared with popular techniques	-	-	-	-	-
Pompe & Bilderbeek (2005)	Prediction	DA, MLM	1369	Belgium	Industrial SMEs	1986-1994
Aziz & Dar (2004)	Comparsion of different prediction models	-	-	-	-	1968-2003
Charitou et al. (2004)	Prediction	LR, MLM	51	UK	Public Industrial Firms	1988-1997
Becchetti & Sierra (2003)	Prediction	MLM, M	13014	Italy	Manufacturing	1989-1997
Tornhill & Amit (2003)	Prediction	LiR	339	Canada	Bankruptcies	1996
Ulrich (2001)	Comparsion of 2 MCMs	M	15538	East Germany	Service Sector	1994-1999
Shumway (2001)	Comparing different models with others	-	-	-	-	-
Laitinen (1992)	Prediction	LR	40	Finland	Industrial	1980-1985

(*) DA: discriminant analysis (two-function, multivariate); FCA: factor/cluster analysis; LR: logistic regression; LiR: linear regression; M: models (risk index, conditional probability, markov chain etc.); MLM: machine learning methods (neural networks, adaboost etc.); T: Tests (mann-whitney test, median test, non-parametric test).

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Different methods have been used and the most commonly used methods are Altman's Z-score, various discrimination analyses, neural networks (NN) and logistic regression. All the specific tests, models, analyses were grouped under one common heading with their common name and this is included in the literature review table (Table 1).

The following provides a comparative overview of the articles presented in Table 1 and their methodological structure. Alfaro et al. (2008) use only different machine learning methods for prediction - mainly Adaboost with Neural Network - and found that Adaboost surpasses Neural Networks. Charitou et al. (2004) analysed machine learning methods, more specifically neural networks together with logistic regression. The prediction of UK business failure was investigated in this paper using different methods and concluded that LR and NN were the most determinant Charitou et al. (2004).

Arroyave (2018) compared most important techniques (Altman Z-score, Korol decision Tree, Discriminant Analysis) for large Colombian industrial firms and found that logit models predict failure most accurately of all the methods used.

Other studies using Altman's Z-score, for example Wetter & Wennberg (2009), Odibi et al. (2015) and Altman et al. (2017) are in our Table 1. Wetter & Wennberg (2009) concluded that the Z-score does not predict bankruptcy with high accuracy, but Odibi et al. (2015) found that the Z-score is equally accurate and does not differ from previous studies. This implies that several studies show that the Altman's Z-score gives an inconsistent result and does not give an equivalent result to other models, and therefore the prediction equation needs more research to find better and more stable methods.

Discriminant analysis (DA) has been used by Vuran (2009), Pompe & Bilderbeek (2005), Ciampi (2017), which we discuss later in this chapter, and Arroyave (2018), which we discussed already.

We also selected studies that have been carried out using factor and/or cluster analysis to add a comparative momentum and complexity to our thesis. For the literature table, we selected two articles from Lukason et al. (2016) and Lukason & Käsper (2017). The articles were different in their context. One examines failure processes in new manufacturing microenterprises Lukason et al. (2016) and the other examines failure prediction in government funded new firms Lukason & Käsper (2017). One focuses specifically on one country, the other has a broader view of Europe as a whole, which already makes them different from each other to show different conclusions. These studies show us that there is a possibility that young firms can go through different failure processes. This shows that the types of firms are different and therefore logit regression may not be accurate because it cannot capture these different failure processes. The study by Lukason & Käsper (2017) shows that the majority of starting young and surviving firms have poor financial ratios in the first years of activity.

Finally, we also selected articles on different methods and different comparative studies. These articles do not examine the prediction of failure using a particular method, but are theoretical, comparing advantages and disadvantages. Balcaen & Ooghe (2006), Gepp (2005) and Aziz & Dar (2008) compare different methods (e.g. DA, models and LR). They were chosen for this thesis because they provide a good overview of the different methods. Veugelers (2008) investigates how innovation can improve market failures in small-medium and large firms from many different perspectives - for example, by size class, whether SMEs are inferior to large firms.

Table 1 shows that the most commonly used method is logistic regression. LR is good for the analysis of different variables Peng (2002). Its advantages are the absence of statistical assumptions, the ease of use of the results (in the form of probabilities) and the ability to highlight the significance of individual variables.

Therefore, Table 2 was constructed, analysing only the articles that dealt with Logistic Regression. From Table 1, 11 articles on Logistic Regression were selected. Three topics are shown in Table 2: Variables Applied, Variables in Models, where the authors have chosen these variables that are more precise and Prediction Accuracy. The accuracy is shown there in percentages or AUC (Area Under Curve). Mostly financial variables were used and some articles also used variables such as corporate governance, which make the predicting more accurate Ciampi (2015). In this thesis, the focus is more on financial variables and therefore only financial variables from these studies are presented in Table 2. It shows all the variables that the authors used in the modelling (variables used) and that were finally included in the models. For example, while Abdullah et al. (2019) included all the variables logic to predict failure, others, such as Vuran (2009), only include statistically significant variables using a stepwise procedure. In articles that use all variables logic, not all variables are significant if their main purpose is prediction. In this case, these variables can be excluded from the models and are not included in the models at all, as done in Lukason & Andresson (2019). Pompe & Bilderbeek (2005) found in their study that a sufficiently large sample is needed to build a reliable predicting model. Vuran (2009) believed that a larger number of variables can significantly increase the predictive accuracy and selected 30 variables for his study. In some articles they omitted very specific variables, for example Charitou et al. (2014) have "(IBt - IBt2-1)/(IIBtI + IIBt2-1I) Change in IB", where IB is "Income before Extraordinary Items" or as in Tong & Saladrigues (2018) "proportion of accounts payable to total liabilities", but most of them are widely used as "Net income to total assets" and this is the variable we use in our calculations. There are a large number of different formulas for financial ratios, which are often only marginally different. The difference in accuracy between small sample studies and large sample studies is not very notable. For example, Laitinen & Suvas (2013) have an accuracy of around 70% with the highest result for Poland, and more or less the same result in Altman et al. (2017), where Poland also has the highest percentage. The accuracy of Lukason & Käsper (2017) and Laitinen (1992) shows that in the second year (T-2) the accuracy decreases and in the following years the decrease accelerates. From the table, it can be seen that Vuran (2009) and Charitou et al. (2004) have reached similar results, only *vice versa*, two or more years before the firm fails. It is notable that, according to Laitinen (1992) and Fuertes et al. (2020), the accuracy percentages of young firms are significantly lower than those of older firms.

To conclude the literature review chapter, most of the articles deal with indicators for only one specific country, and only Laitinen's four articles and Veugelers' (2008) article deal with several countries. Most of the studies used in Table 2 focus only on manufacturing companies, making them uniquely relevant for this thesis. What makes this thesis unique is that no previous research on the prediction of failure of young firms has been specifically conducted for the manufacturing industry.

Table 2

Selection of failure prediction articles using logistic regression: variables applied, variables in model(s) and logit Accuracy (%) (composed by authors).

Article	Variables applied	Variables in model(s)	Logit Accuracy (%)
Fuertes-Callen et al. (2020)	Total Assets; Return on Assets; PROFIT; Debt ratio; Interest coverege ratio; Debt coverage ratio; Cash Flow/Total Liabilities; Working capital ratio; WC; Cash ratio; Revenue per employee; Staff costs per employee	Total Assets; Return on Assets; PROFIT; Debt ratio; Interest coverege ratio; Debt coverage ratio; Cash Flow/Total Liabilities; Working capital ratio; WC; Cash ratio; Revenue per employee; Staff costs per employee	All variables: 62,6%
Munoz-Izquierdo et al. (2019)	Assets; Liabilities and contingencies; Results of the period; Accumulated losses; Information omission; Negative working capital; Subsequent events; Regulation and environment; Management Plan; Going concern; Insolvency proceedings	Assets; Liabilities and contingencies; Results of the period; Accumulated losses; Insolvency proceedings	75% of dataset: 81,4%; 25% of dataset: 79,6%
Abdullah et al. (2019)	Log (total assets); Log (share capital); Total liabilities to total assets; Short term liabilities to total liabilities; Liquidity; Sales to total assets; Earnings before interest and tax to total assets; Net income to share capital; Constatnt	Log (total assets); Log (share capital); Total liabilities to total assets; Short term liabilities to total liabilities; Liquidity; Sales to total assets; Earnings before interest and tax to total assets; Net income to share capital; Constant. (These significancy present in different years).	4-year: 77.5% 3-year: 79,2 %, 2-year: 87,5%, 1-year: 90%
Arroyave (2018)	Profit from sales / total assets; Working capital / total assets; (net income + depreciation) / total credits; perational cost (excluding other operating cost) / current liabilities; Total equity / total credits; (total equity + non-current liabilities) / fixed assets; Revenues / total assets; Current assets / current liabilities; Current liabilities / total assets; Income before taxes / current liabilities; Total assets / total credits; Income before taxes / total assets; Income before taxes / net revenues; Inventories / net revenues; Net income / total assets	Profit from sales / total assets; Working capital / total assets; (net income + depreciation) / total credits; perational cost (excluding other operating cost) / current liabilities; Total equity / total credits; (total equity + non-current liabilities) / fixed assets; Revenues / total assets; Current assets / current liabilities; Current liabilities / total assets; Income before taxes / current liabilities; Total assets / total credits; Income before taxes / total assets; Income before taxes / net revenues; Inventories / net revenues; Net income / total assets	Comp. 1: 2012: 2% 2013: 12 %, 2014: 22%, 2015: 86%. Comp. 2: 2012: 41% 2013: 54 %, 2014: 53%, 2015: 54%. Comp. 3: 2012: 21% 2013 11%, 2014: 14%, 2014: 13%
Tong & Saladrigues (2018)	One plus total assets; Total amount of operating revenues, Total amount of operating revenues (profitabilty); Equity; Indebtness; Liquidity; Sales/Total Assets, liability (loans); Proportion of accounts receivable to total assets; Proportion of accounts payable to total liabilities; Proportion of accounts payable to total liabilities; Entry rate; Concentration rate,;Industry growth rate	Manufacturing: One plus total assets; Profitability; Reciprocoral of indebtness; Reciprocoral of general liquidity; Asset rotation; Corporate venturing; Rate of growth of industrial operating revenues	Failing after age 1: 60,7%; Failing after age 2: 61,2%; Failing after age 3: 62,6%
Altman et al. (2017)	Working capital/Total assets; Retained earnigs/Total Assets; EBIT/Total Assets; Book value of equity/Total liabilities; Market value of equity/Book value of total liabilities; Sales/Total Assets	Working capital/Total assets; Retained earnigs/Total Assets; EBIT/Total Assets; Book value of equity/Total liabilities	Model 1->8 AUCs: 0,743, 0,745, 0,752, 0,760, 0,748, 0, 751, 0,749, 0,771. Highest AUC - Poland 0,908; Lowest AUC - China delisted 0,519.
Lukason & Käsper (2017)	Current liabilities with cash; Current liabilities with current assets; Net income to total assets; Net income to opereting revenue; Total equity to total assets; Opereting revenue to total assets	Current liabilities with cash; Current liabilities with current assets; Total equity to total assets; Opereting revenue to total assets	1-year after becoming active: 63,8 %; 2-year after becoming active: 67, 8%
Ciampi (2015)	Return on equity; Interest charges/bank loans; Return on investment; Turnover/net operative assets; Return on sales Leverage; Value added/turnover; Bank loans/turnover; EBITDA/turnover; Net financial position/turnover; EBITDA/cash flow; Total debts/(total debts + equity); Interest charges/turnover; Financial debts/equity; Interest charges/EBITDA; Total debts/EBITDA;	Return on investment; EBITDA/turnover; Interest charges/turnover; Financial debts/equity	All: 84,3%; Correctly classified 76,4%

	Turnover/number of employees; Equity/long-term material assets; Value added/number of employees; Liquidity; Long term assets/number of employees; Current ratio; Cash flow/total debts; Acid test ratio		
Laitinen & Suvas (2013)	Return on assets ratio (profitability); Quick assets to total assets ratio (liquidity); Equity ratio (solvency); Semi-deviation in the return on assets ratio in two last years (volatility); Total assets (size); Squared total assets (size)	Return on assets ratio (profitability); Quick assets to total assets ratio (liquidity); Equity ratio (solvency); Total assets (size); Squared total assets (size)	71,3% (Min 62% - UK; Max 83,3% - Poland)
Vuran (2009)	Current Assets / Current Liabilities; (Current Assets – Inventories) / Current Liabilities; (Cash + Bank) / Current Liabilities; Sales / Accounts Receivable; Cost of Goods Sold / Inventories; Sales / Current Assets; Sales / Fixed Assets; Sales / Tangible Fixed Assets; Sales / Total Assets; Sales / Total Equity; Gross Profit / Sales; Earnings Before Interest and Taxes / Sales; Net Profit / Sales; Net Profit / Total Equity; Net Profit / Total Assets; Total Debt / Total Assets; Short Term Debt / Total Assets; Long Term Debt / Total Assets; Total Debt / Total Equity Financial Structure Total Equity / Total Assets; Fixed Assets / Total Equity; Fixed Assets / (Total Equity + Long Term Debt); Tangible Fixed Assets / Total Equity; Current Assets / Total Assets; Fixed Assets / Total Assets; Tangible Fixed Assets / Total Assets; Cash Flow From Operations / Interest Expense; Net Sales; Total Equity; Total Assets	1-year: Current Assets / Current Liabilities; Sales / Total Assets; Net Profit / Total Assets; Total Debt / Total Assets; Fixed Assets / Total Equity; Total Assets; Cash Flow From Operations / Interest Expense; Current Assets / Total Assets; Fixed Assets / Total Assets; Tangible Fixed Assets / Total Assets 2-year: (Current Assets – Inventories) / Current Liabilities; Sales / Total Assets; Net Profit / Total Assets; Short Term Debt / Total Assets; Fixed Assets / Total Equity; Total Assets; Current Assets / Total Assets; Fixed Assets / Total Assets; Tangible Fixed Assets / Total Assets	1-year prior: 84,4%; 2-year prior: 82%
Charitou et al. (2004)	Retained Earnings/Total Assets; Shareholders' Equity/Total Assets; Shareholders' Equity/Total Debt; Shareholders' Equity/Total Liabilities; Total Liabilities/Total Assets; Total Liabilities/Net Worth; Cash Flow from Operations/Total Assets; Cash Flow from Operations/Current Liabilities; Cash Flow from Operations/Net Worth; Cash Flow from Operations/Sales; Cash Flow from Operations/Total Liabilities; Debtors/Cash Flow from Operations; Current Assets/Total Assets; Current Assets/Current Liabilities; Current Liabilities/Current Assets; Current Liabilities/Total Assets; Current Liabilities/Net Worth; Current Liabilities/Total Liabilities; Quick Assets/Total Assets; Quick Assets/Current Liabilities; Working Capital/Total Assets; (IBt - IBt2-1)/(IIBtI + IIBt2-1I) Change in IB; Earnings Before Interest & Taxes/Total Assets; Earnings Before Interest & Taxes/Current Liabilities; Earnings Before Interest & Taxes/Fixed Assets; Earnings Before Interest & Taxes/Shareholders' Equity; Earnings Before Interest & Taxes/Total Liabilities; Income Before Extraordinary Items/Fixed Assets; Income Before Extraordinary Items/Sales; Income Before Extraordinary Items/Total Liabilities; Income Before Extraordinary Items/Total Assets; Income Before Extraordinary Items/Shareholders' Equity; Working Capital from Operations/Total Assets; Working Capital from Operations/Net Worth; Working Capital from Operations/Sales; Current Assets/Sales; Stocks/Sales; Net Worth/Sales; Quick Assets/Sales; Sales/Current Assets; Sales/Total Assets; Sales/Fixed Assets; Market Value of Equity/Total Debt; Market Value of Equity/Shareholders' Equity	Retained Earnings/Total Assets; Shareholders' Equity/Total Assets Shareholders' Equity/Total Debt; Shareholders' Equity/Total Liabilities; Total Liabilities/Total Assets; Cash Flow from Operations/Total Assets; Cash Flow from Operations/Current Liabilities; Current Liabilities/Current Assets; Current Liabilities/Total Assets; Quick Assets/Current Liabilities; Working Capital/Total Assets; (IBt 2 IBt21)/(jIBtjþjIBt21j) Change in IB; Earnings Before Interest & Taxes/Total Assets; Earnings Before Interest & Taxes/Current Liabilities; Earnings Before Interest & Taxes/Fixed Assets; Earnings Before Interest & Taxes/Total Liabilities; Income Before Extraordinary Items/Sales; Income Before Extraordinary Items/Total Liabilities; Income Before Extraordinary Items/Total Assets; Working Capital from Operations/Total Assets; Working Capital from; Net Worth/Sales; Market Value of Equity/Total Debt; Market Value of Equity/Shareholders' Equity	1-year prior to bankruptcy: 94%; 2-year prior: 84%; 3-year prior: 70%
Laitinen (1992)	Return on investment; Cash flow to net sales; Financial Assets/Current debt; Stockholders capital to total capital; Cash flow to total debt; Rate of annual growth in net sales; Logarithmic net sales; Net sales to total capital	Return on investment; Cash flow to net sales; Financial Assets/Current debt; Stockholders capital to total capital; Cash flow to total debt; Rate of annual growth in net sales; Logarithmic net sales; Net sales to total capital	Year after foundation: 1. 72,5%; 2. 75%; 3. 77,5%; 4. 78,95%

2. Data and method

The data used in this study originates from the Bureau van Dijk Amadeus database. The data consisted of different financial variables retrieved from 35 European countries and cover the period of 2013 to 2021. Our focus is to get an overview of young manufacturing firms and the classification is from NACE Rev.2[1] section C for manufacturing industry.

After an initial filtering of the data on failed companies, we aggregated the data to exclude companies for which there was no financial information on their activities from the outset. In the first stage, we filtered out companies that started from 2015 onwards, so that only companies that went bankrupt or were declared insolvent in the first five years were included in the sample. The second step for the failed firms was to use in the sample only those firms that had financial variables for at least two years that could be used for logistic regression analysis. The initial sample of 35,056 firms was reduced to 3,987 firms, a significant but also expected reduction as there were many firms in the initial sample for which no financial variables were reported.

The sample of active companies was filtered out to exclude all the companies that have been active for 5 years or more and were established between 2013 and 2015. The number of active companies was reduced from initial 75,070 to 52,835.

To get a better overview of the data and the results, the aggregate model is based on complete data, and in addition, in this study we have highlighted 9 countries out of 35 European countries. The aim is to show how results vary in those countries that contribute most to the data collection for this survey. It should be noted that all 9 countries were selected according to the number of non-active companies, with a minimum value of 100 companies. Table 3 shows, for the 9 countries selected, what proportion of the total number of companies is made up of failed and what proportion of non-failed enterprises.

[1] NACE Rev. 2 - Statistical classification of economic activities in the European Community

Table 3

Failed and non-failed companies sample (composed by authors).

Countries	Failed	Non-failed	Overall
All countries (35 European countries)	3 987	52 835	56 822
Spain	191	3 130	3 321
France	425	1 089	1 514
Croatia	130	1 178	1 308
Hungary	407	1 887	2 294
Italy	1 515	7 681	9 196
Norway	141	845	986
Poland	123	1 277	1 400
Portugal	187	2 267	2 454
Romania	236	3 613	3 849

Logistic regression has been selected as the only method to go deeper into the formulation of failure prediction models in this work, as our aim is to present the accuracy of failure prediction. Table 5 was constructed by applying logistic regression with only single variables for all nine countries. The 9 selected countries were also analysed separately for both T+1 and T+2 periods. The reason for this is to see which variables show the highest and which the lowest accuracy. For Table 6, the model was constructed with all the variables and this was done for the 9 selected countries as well as for all countries combined. It should be mentioned that the failed and non-failed samples are weighted equally. The variables analysed are from the first and second active year of the financial data submission (indicated in the following text as T+1 and T+2). The active year is defined here as the first and second year in which the data for our study were available and therefore data can even come from the 3rd, 4th and 5th year of activity of the companies.

A study by Jackson & Wood (2013) shows that the 5 main methods used in previous studies are: 1. Multivariate Discriminant Analysis (MDA) 2. Logit 3. Neural Networks (NN) 4. Contingent Claims Model 5. Univariate analysis. Top 5 are three statistical methods, one theoretical and one artificial intelligence method Jackson & Wood (2013). All of these are the most used methods and for this study LR was chosen.

The selection of variables as seen in Table 4 were chosen in a combination from three different sources: Laitinen & Suvas (2013), Altman et al. (2017), Lukason & Andresson (2019). The aim for these variables is to provide an overview of liquidity, profitability, productivity and size of companies.

Table 4

Codes and formulas used in this thesis (composed by authors).

Code	**Formula**
CACLTA (liquidity)	(Current assets - current liabilities) / total assets
CCLTA (liquidity)	(Cash - current liabilities) / total assets
LNTA (size)	Ln*total assets
LNOR (size)	Ln*operating revenue
SFTA (solvency)	Total equity / total assets
SFCTA (solvency)	(Total equity - paid in capital) / total assets
ORTA (efficiency)	Operating revenue / total assets
NIOR (profitability)	Net income / (operating revenue + 1[1])
NITA (profitability)	Net income / total assets

[1] +1 added so that the variable would not remain 0 as then it would be unable to calculate the necessary result.

3. Results and discussion

Firstly, we analyse the results in Table 5, which should give a clear overview of which specific variables turn out to be more accurate than the others. The results are presented separately for the failed and the non-failed firms and as a comparison of their arithmetic averages. For clarity, we have marked the overall percentage for each country and for each period T+1 and T+2 in green and red. Green indicates the two most accurate results in the overall and red the two least accurate. This allows the reader to visually observe which indicators are the best and the worst individually.

We can come to quite certain result that the size as well as profitability variables provide the best results. The size variables are LNOR and LNTA and the profitability variables are NIOR and NITA. We see some questionable values for some of the results shown, the first being the T+1 period for Croatia, with the two highest values being ORTA 55.5% and SFCTA 57.5%, or the efficiency and solvency variables. This may be due to country-specific regulations or to the economic dynamics of the different countries, which also supports the claim that the analysis of all countries together does not provide high accuracy, as the low accuracy in some countries can have a significant impact on the final results. We also see that for Italy, the efficiency variable ORTA is 54.7% in the T+1 period. In the T+2 period, the most accurate variables are mostly the same, with the size and profitability being the most accurate variables. In the case of Italy, we see some values that indicate that the liquidity variable CCLTA 55.6% is the most accurate for the T+2 period. For the T+2 period, we can also note that the Polish liquidity variable CACLTA 56.4% and the Romanian solvency variable SFCTA 58.1% show a higher accuracy.

Regarding the least accurate results found in the T+1 and T+2 periods for specific variables, in the T+1 period we see a pattern that not so accurate results can be found for all variables except for the profitability variables NIOR and NITA, which show only one low result for Croatia NIOR of 50.5%. For the T+2 period, we also see the results that we claimed for the most accurate results, that the profitability and size variables provide the best results. While in the T+1 period we find multiple low results for the size variable, we find only two results in the T+2 period in Poland, with a LNOR of 49.2%, and in Romania, with a LNOR of 48.6%. The profitability variables also show good results in the T+2 period, as in Italy there is only one low result, as NITA was 50.8%. In conclusion, liquidity shows the least accurate results and by comparing the T+1 and T+2 periods, we can see a significant increase in the number of low results for the efficiency variable ORTA, as in the T+1 period we find one low result for France (49.1%) and in the T+2 period we find a total of four low results: 51.4% for Croatia, 50.5% for Hungary, 51.1% for Romania and 53.6% for Portugal.

The main aim of our study to predict the failure of young manufacturing firms can be best analysed in Table 6, which illustrates an overall comparison between all variables, giving us results for failed, non-failed and overall prediction accuracy. The data are presented for three different time periods: T+1, T+2 and two time periods in total. Also, all the results are presented for the selected 9 countries as well as for all countries covering 35 European countries, including the 9 that are also presented separately.

Following the same visual analysis as in Table 5, we marked the two best results in green and the two lowest results in red. The highest results for all periods are displayed for France and Portugal. The results for France are very consistent, with T+1 at 65.9%, T+2 at 66.1% and a combined result of 67.0%. Portugal's results are even higher: T+1 is 67.3%, T+2 is 67.2% and the combined result of T+1 and T+2 is 68.3%. Several countries have low results, but the lowest is Italy with T+1 at 56.8%, T+2 at 56.6% and a combined score of 56.5%.

If we also look at the results for the failed and non-failed columns, we see that the failed companies have higher accuracy, which is due to the fact that in the early years of young manufacturing companies, the financial variables are equally bad for future failed and non-failed companies, as the authors expected. In addition, we have a column of results for all countries because we see that the difference between failed and non-failed companies is very large. This is also due to the fact that we have a large number of countries and country-specific regulations and economic dynamics are different, so it is not feasible to do a multi-country analysis. In other words, when all countries are lumped together, the performance of some survivors is similar to the failures in other countries and only a very small number of well performing companies from only a few countries stand out. When we look at the results from a country-specific perspective, they are more accurate, and hence one of the main conclusions of our study is that it is better to approach individual countries separately rather than using international data, because the data vary from country to country and the results are incomplete in an international context. That claim is also supported by the study by Altman et al. (2017), who argue that although the model shows decent results in some countries, the accuracy of the classification can be improved by country-specific estimation.

Table 5

Accuracies of prediction models based on single variables from periood T+1 and T+2 for nine countries individually (composed by authors).

T+1																											
Variable	**Spain**			**France**			**Croatia**			**Hungary**			**Italy**			**Norway**			**Poland**			**Romania**			**Portugal**		
	Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %		
CACLTA1	47.1	57.3	**52.2**	51.2	51.7	51.5	44.2	59.7	52.1	58.7	39.4	**49.1**	55.2	48.5	**51.9**	38.2	62.3	**50.3**	52.5	58.4	55.5	59.7	49.8	54.7	61.2	47.5	54.7
CCLTA1	38.9	65.9	52.5	22.6	77.9	50.8	42.1	59.8	51.0	55.2	50.4	52.8	64.5	44.1	54.3	52.6	52.8	52.7	13.4	86.6	50.7	58.4	41.4	**49.9**	57.7	49.2	**49.9**
LNOR1	62.8	55.2	**59.0**	56.0	31.5	**43.7**	70.0	35.7	52.8	68.8	56.4	**62.6**	75.8	32.2	54.0	73.0	34.3	53.7	61.8	43.0	52.4	52.9	45.4	**49.2**	79.7	50.1	**49.2**
LNTA1	57.1	54.2	55.6	61.4	61.0	**61.2**	58.5	41.1	**49.8**	59.5	61.6	60.5	52.9	46.4	**49.6**	62.1	48.5	**55.3**	41.5	46.8	**44.1**	50.8	54.3	52.6	70.6	62.6	52.6
NIOR1	89.2	27.2	**58.9**	82.2	29.0	56.3	94.6	6.4	**50.5**	81.7	39.5	**61.1**	88.6	16.4	53.7	80.5	21.8	52.1	68.7	44.8	**57.0**	77.9	31.9	**55.4**	57.8	57.9	**55.4**
NITA1	53.3	57.9	55.6	62.6	52.0	**57.3**	20.3	86.7	53.3	59.3	60.7	60.0	50.1	60.6	**55.4**	52.3	63.7	**58.0**	54.4	62.7	**58.5**	53.7	63.9	**58.8**	56.9	56.5	**58.8**
ORTA1	40.2	65.7	53.2	30.4	67.3	**49.1**	51.3	59.7	**55.5**	43.6	69.2	56.6	48.4	61.0	**54.7**	42.9	65.6	54.3	27.0	81.8	55.7	48.5	58.2	53.3	50.9	62.6	53.3
SFCTA1	44.4	63.2	53.9	55.4	54.3	54.9	50.0	64.9	**57.5**	81.0	25.4	53.7	84.5	21.0	52.9	70.6	34.1	52.3	56.3	52.9	54.6	76.3	32.9	54.7	60.5	58.3	54.7
SFTA1	37.6	60.4	**49.0**	70.3	31.3	50.8	38.3	63.5	51.2	100.0	1.0	**50.5**	67.6	37.3	52.4	50.4	50.4	**50.4**	41.7	56.7	**49.2**	53.2	53.0	53.1	61.9	53.8	53.1

T+2																											
Variable	**Spain**			**France**			**Croatia**			**Hungary**			**Italy**			**Norway**			**Poland**			**Romania**			**Portugal**		
	Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %			Failed; Non-failed; Overall %		
CACLTA2	49.2	54.6	51.9	28.7	72.6	**50.8**	69.3	46.3	58.0	62.1	40.7	51.5	25.0	73.1	**49.1**	40.1	59.5	**49.9**	46.8	65.7	**56.4**	60.0	50.2	55.1	77.2	30.0	**54.2**
CCLTA2	40.3	55.0	**47.7**	20.8	82.6	52.5	59.8	49.2	**54.6**	65.3	40.7	53.2	63.9	47.3	**55.6**	37.8	63.8	50.8	2.8	97.5	**51.0**	52.7	52.5	52.6	79.1	28.3	54.4
LNOR2	63.9	53.7	**58.8**	23.3	80.0	51.7	64.6	53.7	59.1	69.8	55.8	**62.8**	63.3	41.3	52.3	67.4	33.7	50.6	62.3	36.2	**49.2**	55.6	41.7	**48.6**	76.7	54.4	**65.5**
LNTA2	50.8	56.3	53.5	63.8	63.3	**63.5**	56.9	54.6	55.7	59.9	60.3	**60.1**	50.1	52.3	51.2	61.0	48.6	**54.8**	59.0	52.1	55.5	55.4	48.9	52.1	70.0	64.1	**67.0**
NIOR2	89.9	23.1	**56.9**	57.0	53.5	**55.3**	68.0	53.9	**61.1**	83.0	32.8	59.0	92.5	14.0	**54.1**	87.1	17.8	**53.5**	61.5	49.3	**55.6**	56.5	58.9	57.6	87.3	29.7	59.5
NITA2	55.9	51.6	53.7	50.5	59.0	54.7	62.7	59.9	**61.4**	61.8	56.2	59.1	38.0	63.5	**50.8**	68.2	35.5	51.9	43.0	66.6	55.0	61.0	59.4	**60.2**	89.1	26.4	59.2
ORTA2	43.5	59.5	51.6	43.1	61.3	52.3	47.2	55.6	**51.4**	28.2	71.3	**50.5**	45.5	60.1	52.9	37.4	67.0	52.7	27.8	77.4	53.5	42.0	60.1	**51.1**	56.1	51.0	53.6
SFCTA2	46.0	60.7	53.3	50.8	54.1	52.4	60.3	52.7	56.5	69.3	46.5	58.1	43.2	55.9	49.5	65.2	38.1	51.6	47.3	56.2	51.8	65.9	50.0	**58.1**	82.1	36.4	60.1
SFTA2	42.9	56.0	**49.4**	40.5	58.9	**49.8**	60.3	52.7	56.5	71.0	29.0	**50.3**	65.0	40.0	52.5	11.0	86.3	**48.9**	42.0	62.1	52.2	58.4	52.1	55.3	80.3	35.4	58.6

Although we reached the same conclusion as Altman et al. (2017), suggesting that country-specific analysis provides greater accuracy, we do not have similar results. This is due to the different data used in the model, as Altman et al. (2017) focus on older companies, and therefore have a higher accuracy compared to the analysis of young companies. To illustrate the different results with the data, we can compare the results for our selected 9 countries with the results of Model 2 in Table 6 of Altman et al. (2017). The results of our study were as follows: ES 62.2%; FR 67.0%; HR 65.0%; HU 65.0%; IT 56.5%; NO 62.1%; PL 63.4%; RO 61.4%; PT 68.3% compared to the results of Altman et al. (2017): ES 76.7%; FR 79.9%; HR 85.8%; HU 74.3%; IT 81.0%; NO 74.1%; PL 89.7%; RO 77.3%; PT 75.7%. The article also suggests that young companies are more likely to be classified as bankrupt than older companies, which is understandable as this is also shown by the difference in our results.

Another important finding of this study, based on the results presented in Table 6, is that although the second year results are more accurate, meaning that the financial ratios of the problematic or failing companies have fallen significantly and the active companies stand out more with better financial results, giving a clearer indication of the difference between the two, the results of the first year are already convincing that from the outset there are only a small number of companies that would be acceptable in the eyes of a conservative credit institution.

There are only a small number of companies that can be described as highly potential to succeed, as also noted in Jackson & Wood (2013). This was also referred to in our study, as the difference between failed and non-failed companies is not large, but there are a small number of companies from a small number of countries with very good financial results from the outset. The article also puts forward the idea that for a company to survive in the future, all financial ratios need to achieve excellent values.

In support of our findings, we find similar results in Fuertes-Callén et al. (2020). The article states that the training sample scored 65.9%, with 182 failed and 182 non-failed companies in the sample, and the test sample scored 62.6%, with 182 failed and 5,621 non-failed companies. The test sample result of 62.6% compared to our survey result for Spain of 62.2% also confirms our results for specific countries. This article also concentrates on newly founded firms and covers a significant sample of 6,167 companies from Spain, as the specific sample for Spain in our study is 3,321 companies. This study also concludes that size and profit variables can be considered as the most accurate variables for predicting the future of companies.

Similar accuracy results were also found by Lukason & Käsper (2017), although their study focused on predicting the failure of government funded start-up firms. It should be noted that this article also used pre-selected companies, which are expected to have lower accuracy. In their study, the result was 63.8% for T+1 and 67.8% for T+2, although our average result is lower than 63.8%, as our study was 61.4% for T+1 and 61.8% for T+2, and close to 63.5% for the combined period. When we look at countries separately in our analysis, we see that most countries give similar results.

Comparing our study with that of Laitinen (1992), we see many similarities as the focus is on young companies, but the sample size is significantly different as our study has a sample of 3,987 failed and 52,835 non-failed companies, giving us a broad analysis. Laitinen (1992) uses 20 failed and 20 non-failed companies in his article, which allows one sample result to have a significant impact on the overall result. The accuracy for the young companies reported in this article varies from 57% to 76%, which means that our accurancy range from 56.5% to 68.3% is easily comparable between each other. Companies of similar age were used, as both studies included failed companies that went bankrupt or were declared insolvent within five years after its establishment.

Table 6

Accuracies of prediction models based on all variables from period T+1; T+2; T+1 and T+2 for nine countries individually as well as all countries combined (composed by authors).

Country	**T+1 and T+2**			**T+1**			**T+2**		
	Failed %	Non-failed %	Overall %	Failed %	Non-failed %	Overall %	Failed %	Non-failed %	Overall %
All countries	93.2	19.9	64.9	91.7	17.4	62.6	93.9	20.6	64.8
Spain	70.0	54.1	62.2	65.6	53.5	59.6	65.6	57.0	61.4
France	74.3	60.0	**67.0**	70.5	61.4	**65.9**	73.0	59.4	**66.1**
Croatia	73.1	56.2	65.0	60.9	55.2	58.1	79.0	46.8	63.6
Hungary	69.1	59.9	64.6	69.1	59.4	64.3	69.1	57.4	63.3
Italy	70.9	41.1	**56.5**	72.0	40.5	**56.8**	70.1	42.5	**56.6**
Norway	67.4	56.6	62.1	65.4	49.0	**57.3**	72.6	46.8	59.8
Poland	43.9	79.0	63.4	60.5	66.9	63.9	40.3	73.1	**57.5**
Romania	69.3	52.9	**61.4**	67.7	47.9	58.1	60.7	54.8	57.8
Portugal	81.3	51.2	**68.3**	78.2	54.2	**67.3**	80.9	50.9	**67.2**

Conclusion

In recent years, there has been an increasing focus on the prediction of failure of young companies; although the prediction of failure of young manufacturing companies in Europe has not yet been much addressed. Therefore, this topic was chosen in this work in order to go deeper into it.

Although the authors of this thesis obtained a large amount of data from the Amadeus database, most of the companies, especially the failed ones, had to be excluded because there was not enough information on them. First, we looked to see whether the companies had sufficient data on current assets and net income covering two years to allow us to get analytical results.

If we consider the analysis of the data across countries as a whole, there are a lot of inaccurate results because for many young businesses it is not possible to distinguish in the first few years whether they are failing or not, and therefore the result is very similar.

In particular, our findings in the present study support Altman et al. (2017) that country-specific surveys show better results due to different requirements and criteria resulting from country-specific characteristics. The second finding is supported by a recent study in this area by Fuertes-Callén et al. (2020), which also focuses on young companies and shows that if profitability variables show good results, there is a high probability that the company will not fail. This conclusion can also be found in a number of other articles referenced in this study.

To go further with this thesis, this can be achieved in several ways. In future studies, the accuracy of failure prediction can be approved by using only individual countries or a smaller number of countries instead of European-wide data. Some information about countries may be very specific, for example, the success of some board members may come from previous companies, which may affect the mediocre accuracy. The same thesis can be done in the future with the same design, but instead of logistic regression, other most accurate methods (NN, machine learning, etc.) can be used.

In previous years, similar studies have been carried out, but with different target groups (industries). A future study could analyse in the same way as this thesis and check whether the main results would be the same if different target groups were chosen.

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Resümee

NOORTE TOOTMISETTEVÕTETE EBAÕNNESTUMISE PROGNOOSIMINE: EUROOPA RIIKIDE NÄITEL

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Viimastel aastatel on üha enam keskendutud noorte ettevõtete ebaõnnestumise prognoosimisele; kuigi noorte tootmisettevõtete ebaõnnestumise prognoosimisega Euroopas ei ole veel palju tegeletud. Seetõttu valiti käesolevas töös see teema, et sellesse rohkem selgust saada.

Kuigi käesoleva töö autorid said Amadeuse andmebaasist suure hulga andmeid, tuli enamik ettevõtteid, eriti ebaõnnestunud ettevõtted, välja jätta, sest nende kohta ei olnud piisavalt teavet. Kõigepealt uurisime, kas ettevõtetel on küllaldaselt andmeid käibevara ja puhaskasumi kohta, mis hõlmavad kahte aastat, et oleks võimalik saada analüütilisi tulemusi.

Kui me vaatleme andmete analüüsi riikide lõikes tervikuna, on palju ebatäpseid tulemusi, sest paljude noorte ettevõtete puhul ei ole esimestel aastatel võimalik eristada, kas nad ebaõnnestuvad või mitte, ja seetõttu on tulemused väga sarnased.

Eelkõige toetavad käesoleva uuringu tulemusi Altmani jt (2017) järeldused, et riigipõhised uuringud näitavad paremaid tulemusi, mis tulenevad riigispetsiifilistest eripäradest tulenevatest erinevatest nõuetest ja kriteeriumidest. Teist järeldust toetab Fuertes-Callén jt (2020) hiljutine uuring selles valdkonnas, mis keskendub samuti noortele ettevõtetele ja millest võib järeldada, et kui kasumlikkuse muutujad näitavad häid tulemusi, on suur tõenäosus, et ettevõte jääb püsima. Seda järeldust võib leida ka mitmetest teistest käesolevas lõputöös kasutatud artiklitest.

Käesoleva uurimistööga saab jätkata mitmel viisil. Tulevikus saab teha uuringuid ebaõnnestumise prognoosimise täpsuse parendamiseks, kui kasutada kogu Euroopat hõlmavate andmete asemel ainult üksikuid riike või väiksemat arvu riike. Mõned andmed riikide kohta võivad olla väga spetsiifilised, näiteks mõne juhatuse liikme edu võib pärineda varasematest ettevõtetest, mis võib mõjutada keskmist täpsust. Tulevikus võib jätkata uuringuid sarnase ülesehitusega, kuid logistilise regressiooni asemel võib kasutada muid suurema täpsusega meetodeid (NN, masinõpe jne).

Varasematel aastatel on tehtud sarnaseid uuringuid, kuid erinevate sihtrühmadega (tööstusharud). Tulevastes uuringutes võiks viia läbi sarnase analüüsi ja kontrollida, kas peamised tulemused oleksid samad, kui valida erinevad sihtrühmad.