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FAILURE PREDICTION OF EUROPEAN HIGH-TECH COMPANIES

Master’s thesis

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Name and signature of supervisor...

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We have composed this master's thesis independently. All materials, viewpoints from literature and other sources used to write this thesis have been referenced.

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Abstract

The aim of this thesis is to develop a model for predicting the failure of high-tech and medium-high tech companies from different European countries. This study uses firm-level data from the Bureau van Dijk's Amadeus database and includes the financial information of 32,929 firms. The data were collected from the financial statements of the companies for the period 2012–2017 and logistic regression was used as the analysis method. Findings indicate that the accuracies of individual variables across countries are not very high and there are large differences in the accuracies of individual ratios when comparing non-failed and failed firms. Aggregate accuracies for all ratios within country and across countries show that the most accurate predictions are obtained for non-failed firms using the ratios for the preceding two years combined. The practical value of this work lies in the knowledge of the relevant variables, which allows companies to focus in a timely manner on aspects that have determined failure in the past. Subsequent works should attempt to use a larger sample of European countries and include other variables in addition to financial ratios.

Keywords: failure prediction, high-tech companies, manufacturing, logistic regression, pan-European.

CERS: S181, S190, S192

1. Introduction

Failure prediction has attracted scientific interest for a long time, as the development of more accurate models gives valuable information to entrepreneurs, partners, shareholders, investors, venture capitalists, and many others. The term "survival prediction" is generally associated with one specific method in the literature, namely the duration model, one of the best known examples of which is the Cox regression (Luoma & Laitinen, 1991). The concept of "failure", in turn, has been treated in very different ways, such as any exit of firms from the market (Altman et al., 2017) or only the exit of insolvent firms (e.g. du Jardin, 2017). Research in the area of failure prediction is mainly based on a legal event, i.e. the date of the insolvency proceedings or the known deletion date (Lukason et al., 2016; Altman et al., 2017).

To predict the likelihood of such a negative event, researchers have developed a number of different models (Balcaen & Ooghe, 2006). Failure has been described to be a positive phenomenon, which brings about market adjustment as a result. Enterprises with inadequate financial health will cease their activities and free up resources previously held by other companies (Burksaitiene & Mazintiene, 2011, p. 138).

Several previous works have studied failure prediction based on the example of specific size, classes, countries or a combination of the above. To the authors' knowledge, predicting the failure of high-tech and medium-high-tech (hereinafter HMT) companies across Europe has not been addressed in the earlier scientific literature. In addition, it is worth pointing out that there is no universal theory of failure and that researchers have used different approaches and models to study the phenomenon. A more general overview of the various surveys, with sample sizes, used models and accuracies, is provided in Table 1 of this thesis.

The aim of this thesis is to develop a model for predicting the failure of high-tech and medium-high-tech companies from different European countries.

This study is divided into the following parts: literature overview covering the theoretical background to the models and variables in previous literature; the data and methods explaining the empirical work that was carried out; and the results and discussion followed by concluding remarks.

2. Literature review

Over the years, a lot of failure prediction models and methods have been created. With company financial information, it is possible to predict failure with high accuracy (Arroyave, 2018). Nevertheless, external causes of failure (for example economic crisis) can lead both successful and less successful companies to bankruptcy (Arroyave, 2018). For this study, useful literature on business failure was found through literature reviews (Balcaen & Ooghe, 2006; Dimitras et al., 1996; Pretorius, 2009; Ravi Kumar & Ravi, 2007) and database searches using relevant keywords (e.g. failure prediction, bankruptcy, business failure, financial distress). The literature reviews span from the 1930s to 2009.

In this thesis, all previous research articles on the failure prediction of industrial companies have been used. All the previous works deal with some definition of business failure of which insolvency is the most common. The articles were found using the search terms or keywords mentioned above. However, this does not preclude the possibility that some of the relevant works have not been reviewed. Machine learning is widely used in failure prediction nowadays. An important factor, especially when machine learning is used, is that the sector covered in that work may not be clear. The works used in this study do not claim to represent all the failure studies and the used methods. The main aim is to create a cross-section of the models used in failure prediction. There are several other methods used in failure prediction articles, but they have not been used to specifically study industrial sector companies and are therefore not included in this thesis.

In the previous literature (Table 1), different data collection periods (4 to 19 years) have been used. Sample sizes vary from approximately 32 companies to 3,4 million. Studies used in this comparative table cover the period from 1966 to 2019. Also, a wide range of different approaches and methods are covered, for example discriminant analysis (Altman, 1968), regression analysis (Laitinen & Suvas, 2013) and hybrid combination of different analysis (Lin & McClean, 2001).

Table 1. Previous studies of failure prediction: country of origin, time of study, sample size, methods applied, accuracy percentage and forecasting horizon in years (composed by authors)

Studies	Country of origin	Years	Sample size	Model (1)	Accuracy % / forecasting horizon
Hosaka (2019)	Japan	2002–2016	2062	CNN	91.8% / t-4
Barboza et al. (2017)	USA	1985–2013	13433	RF	87.06% / t-1
Altman et al. (2017)	31 European countries + 3 non-European countries	2002–2010	34	LR	82.3%
Williams (2016)	UK	1999–2008	1587	NN	90.5%
Fedorova, Gilenko, and Dovzhenko (2013)	Russia	2007–2011	1332	ANN	88.8% / t-4
Laitinen and Suvas (2013)	30 European countries	2002–2010	3,430,000	LRA	71.09% / t-1
Ravisankar, Ravi, and Bose (2010)	-	2000	240	NN, GP	95.42% / t-1
Gimmon and Levie (2010)	Israel	1991–2001	193	CO	79.3% / t-7
Kim and Kang (2010)	Korea	2002–2005	1458	NN	76.47% /t-1
Chandra, Ravi, and Bose (2009)	-	2000	240	RF + SVM + MLP	93.33 % t-1
Pompe and Bilderbeek (2005)	Belgium	1986–1994	1369	NN	80% / t-1 67% / t-5
Darayseh, Waples, and Tsoukalas (2003)	USA	1990–1997	220	LA	87.82% / t-1 69.23% / t-5
Becchetti and Sierra (2003)	Italy	1989–1991 1992–1994 1995–1997	4194 4714 4106	LA	64.94% / t-1 35.69% / t-2 41.79% / t-3
Jinwoo Baek and Sungzoon Cho (2003)	Korea	1994–2000	662	AANN	59.46% / t-1 36.36% / t-3 Total: 79.4%
Lin and McClean (2001)	UK	1880–1999	1133	Hybrid 1 (DA, LG, NN) Hybrid 3 (LG, C5.0 = DT)	89.6% / t-1
Dunne and Hughes (1994)	UK	1975–1985	2422	LiRA	88% / t-5
Altman, Haldeman, and Narayanan (1977)	USA	1969–1975	111	QDA LDA	96.2% / t-1 69.8% / t-5
Blum (1974)	USA	1954–1968	230	DA	95% / t-1 80% / t-2

					72% / t-3 80% / t-4 69% / t-5
Deakin (1972)	USA	1964–1970	32	DA	87% / t-1 82% / t-3
Altman (1968)	USA	1946–1965	66	MDA	95% / t-1 36% / t-5
Beaver (1966)	USA	1954–1964	158	DCT	87% / t-1 78% / t-5

(1) DCT: dichotomous classification test; DA: discriminant analysis; DT: decision tree; LDA: linear discriminant analysis; MDA: multivariate discriminant analysis; QDA: quadratic discriminant analysis; LiRA: linear regression analysis; AANN: auto-associative neural network; LA: logit analysis; LG: logistic regression; LRA: logistic regression analysis; RF: random forest; SVM: support vector machines; MLP: multilayer perceptrons; NN: neural network; CNN: convolutional neural networks; CO: correlation analysis; GP: genetic programming; ANN: artificial neural network.

Balcaen and Ooghe (2006) have pointed out that the most frequently used models are logistic regression (LR) and multiple discriminant analysis (MDA). Table 1 also shows that regression analysis and discriminant analysis are the most popular models through the article studied. The most used statistical tool for failure prediction – multiple discriminant analysis – was first used by Altman (1968). Nowadays, machine learning and logistic regression are used more frequently. Recent studies use more and more complex models with the goal to achieve higher accuracy in business failure prediction and they have achieved a high degree of accuracy – 91.8% (Hosaka, 2019). By using artificial neural network, the result is an algorithm that helps to model sophisticated patterns and predictions (Mahanta, 2017). In Table 1, the most recent studies have used the neural network model. The growing popularity of this model is also confirmed by Ravi Kumar and Ravi (2007:24). The success of the neural network model is likely to be supported by the fact that information technology is constantly evolving and users are more aware of the different possibilities.

Seven of the twenty studies are based on data from the USA. A comprehensive international review of failure prediction was put together by Altman and Narayanan (1997). Their review covered failure prediction models, sample size, used variables/financial ratios, forecasting horizon and accuracy of results in 22 countries. This overview is used later in this work to compare country-specific results. In Table 1, Laitinen and Suvas (2013) and Altman et al. (2017) were the only ones to use multiple countries in their research. This thesis is likely to offer a good basis for comparison and its results may show certain similarities with Laitinen and Suvas (2013) and Altman et al. (2017).

In Table 2 below, the most important variables of specific studies are pointed out. Table 2 contains fewer articles than Table 1 because Table 2 does not reflect studies where the importance of variables was not clearly presented. Table column titles are based on Lukason et al. (2016). Formulas used in Table 2 have not been changed and are in their original form. Due to that, formula similar in content can occur in the table in several different forms (net working capital/net capital, medium- and long-term debt/long term debt).

Table 2. Previous studies of failure prediction: variables significant in models (composed by authors)

Author	Profitability	Liquidity	Solvency/Financial structure/Leverage	Other
Williams (2016)	REV-CO			
Altman et al. (2017)	EBIT/TA			
Laitinen, Suvas (2013)	ROA	QUIKTA	EQ	Size: TA Volatility: SA
Ravisankar, Ravi, and Bose (2010)			LTD/TA	
Kim, Kang (2010)	OI/TA		EBITDA/IE	
Pompe & Bilderbeek (2005)	PAT/TA		CF/TD	Activity: PAT/TU
Becchetti, Sierra (2003)	EBIT/TD; OP/TA	NWC/MLTD	TD/TA	
Baek & Cho (2003)	EBIT/TA	WC/TA	RE/TA; MC/TD	Turnover: S/TA
Dunne, Hughes (1994)				Age, size, growth rate
Altman, Haldeman, Narayanan (1977)	ROA			Capitalization: CoE/TC Stability of earnings: ESR
Blum (1974)		NQA/I		Variability: standard deviation of net income over a period Financial performance: Quick flow ratio

Deakin (1972)	ROA		CF/TD; TD/TA	
Altman (1968)	EBIT/TA	WC/TA	TE/TD; RE/TA	Turnover: S/TA
Beaver (1966)	NI/TA		TD/TA	

ROA: return on Assets; QUICKTA: quick assets to total assets ratio; EQ: equity, TA: total assets; SA: semi-deviation of ROA; OI: ordinary income; EBIT: earnings before interest and taxes; EBITDA: earnings before interest, taxes, amortization and depreciation; IE; interest expenses; PAT: profit after taxes; CF: cash flow; TD: total debt; TU: turnover; WC: working capital; RE: retained earnings; S: sales revenue; MC: market capitalization; CoE: common equity; TC: total capital; ESR: earnings stability ratio; NI: net income; MLTD: medium and long-term debt; NWC: net working capital; OP: operating profit; NQA: net quick assets; I: inventory; ROA: return on assets; TE: total equity; LTD: long-term debt; REV: revenue; CO: cost.

Failure prediction studies are mostly based on financial ratios. The selection of variables is important, as one combination of financial ratios (or other variables) may have better results in failure prediction than another. One of the key issues in failure predicting is to find the combination of variables providing the highest accuracy.

Beaver (1966) was the first to write about failure prediction and also the first to use ratio analysis for failure prediction. Despite the small sample (a total of 158 firms), he noticed differences between failed and non-failed firms and pointed out that not all ratios predicted equally well (Beaver, 1966).

Unlike others, Aspelund et al. (2005), Dunne and Hughes (1994) used non-balance sheet data as variables instead of financial ratios: size of team, team heterogeneity, company age, radicalness of the technology base.

The most widely used liquidity ratio in failure prediction is working capital/total assets. This ratio can identify potential corporate distress. If the ratio is negative, difficulties leading to short-term liquidation may occur. A positive ratio is a sign of sufficient current assets to cover short-term liabilities. The most used ratio in the column “Solvency/Financial structure/Leverage” is total debt/total assets, which represents leverage. The higher value of this ratio is associated with a higher risk of failure.

The most frequently used balance sheet item in financial ratios is total assets. As assets begin to decline in the process of failure, this item is, so to say, organically linked to business failure. More attention must also be paid to the variables and financial ratios used in the transnational failure prediction articles (Altman et al. 2017; Laitinen and Suvas 2013), because there may be similarities to the present work and they may help to understand and compare results.

In summary, several directions can be pointed out in which the present work differs from previous studies. Failure prediction is mostly focused on a single-country sample and does not cover wider selection. The current study uses the concept of business failure more broadly, including all companies that have closed down, including those voluntarily dissolved. The work of Laitinen and Suvas (2013) deals with failure prediction in different European countries, but is still not all-inclusive. The current study uses a wider definition for business failure prediction. Also, Laitinen and Suvas (2013) have not paid elevated attention to the HMT sector. The present work shows the benefit of individual financial variables in failure prediction, which similar studies usually neglect.

3. Data and methodology

This study uses the firm-level data from Bureau van Dijk's Amadeus database. The data was collected from the financial statements of the companies for the period 2012–2017. Later years (2018–2019) have been excluded from the study due to the lack of information about them at the time of data retrieval and, as a result, the financial ratios were often not calculable.

The definition of company failure is not unambiguous. According to Cochran (1981), bankruptcy by court order is only a fragment of business failure. Also other definitions of business failure cover a large part of the population of failed companies (Cochran 1981). Therefore, it is important not to exclude these other definitions from the population when dealing with business failure. Pretorius' (2009) work shows how differently business failure has been defined in previous studies, from ordinary bankruptcy to closing or exiting the industry. If only businesses in bankruptcy are used in the sample, there is a risk to underestimate the population of problematic businesses.

This work involves all companies that have closed down: the status of the company (according to the Amadeus database) may be in liquidation, bankruptcy, or simply dissolved. Liquidated companies can also be voluntarily liquidated, which means all companies that have been closed (exited) have been included in the study. Studies (Bhattacharjee et al., 2009; Greenaway et al., 2009) have shown that voluntary liquidations can be considered as a failure. Similar methodology has also been used in previous literature (e.g. Laitinen & Suvas, 2013), where in a pan-European study, companies were divided into failed or survived groups, regardless of the reasons for liquidation.

The precondition for the selection of enterprises is that it is classified in Section C according to the NACE classification, meaning it is a manufacturing company. In view of the aim of the thesis, to predict the failure of HMT companies, the selection was narrowed down to firms belonging to classes 20 (Manufacture of chemicals and chemical products), 21 (Manufacture of basic pharmaceutical products and pharmaceutical preparations), 26 (Manufacture of computer, electronic and optical products), 27 (Manufacture of electrical equipment), 28 (Manufacture of machinery and equipment), 29 (Manufacture of motor vehicles, trailers and semi-trailers) or 30 (Manufacture of other transport equipment).

We had to exclude countries that did not have enough data (at least 200 failed cases) during the period under review. As a result, companies from six countries (Russia, the United Kingdom, France, Germany, Italy and Hungary) were included in the research. Failed companies (6371 in total) is the whole population and non-failed (26,558 in total) is a randomly chosen sample from the countries mentioned above. Since the sample of failed companies is the whole population, the hold-out sample is not used and models are composed based on the whole population. As the number of cases in Russia was significantly higher than in other countries, weighting had to be used in the analysis of countries in order to balance the frequencies between the countries. In addition, we weighted the samples of failed and non-failed companies to obtain the same importance in the analysis. More detailed results of countries and samples are presented in Table 3.

Table 3. Structure of failed and non-failed companies in the research data (composed by authors)

Country	Failed	Non-failed
France	902	1897
Germany	337	1897
Hungary	418	1897
Italy	2786	3794
Russia	1704	13,279
United Kingdom	224	3794
Total	6371	26,558

For this study, logistic regression has been chosen as the statistical method for composing prediction models. Ohlson (1980, p. 112) has suggested that a logistic regression model would be more rational in predicting failure than a multivariate discriminant analysis model. Ciampi (2015) has concluded that the main benefit of logistic regression ahead of machine learning is the fact that signs and significances of included variables can be followed.

The choice of variables was based on the main financial ratios used in the previous literature, which characterize the company's liquidity, profitability, solvency and efficiency (see the formulas, ratio dimensions and codes used in Table 4). For example, the variables used by Lukason and Andresson (2019, p. 5) in finding failure processes were included, excluding those in the cash flow statement as they are not included in Bureau van Dijk’s Amadeus database. Although several other financial ratios have been used in previous studies, Lukason and Andresson (2019) have indicated that the financial ratios used in their work represent the most common domains in previous failure studies. In addition, financial ratios for which some countries did not have the necessary entries in the data, were also removed.

Table 4. Coding and formulas of financial ratios used in the thesis

Dimension	**Code**	**Formula**
Liquidity	CCLTA	(Cash and cash equivalent – current liabilities) / total assets
Liquidity	CACLTA	(Current assets - current liabilities) / total assets
Profitability	NITA	Net income / total assets
Profitability	NIOR	Net income / operative revenue
Solvency/capital structure	SFTA	Shareholder fund / total assets
Solvency/capital structure	CLTA	Current liabilities / total assets
Solvency/capital structure	EBITFINOR	(EBIT – EBT) / Operating revenue
Efficiency	ORTA	Operative revenue / total asset

Source: the table is largely based on Lukason and Andresson (2019) with one ratio added and 3 omitted, while modifications have also been made into dimensions, codes and formulas.

4. Results and discussion

First, we analyze the accuracy of a failure model across different financial ratios on a univariate principle. We take a closer look at the ratios that give the highest prediction accuracy, and those that are the most inaccurate. The results are displayed on both inter-country and by-country basis and compared with the median rank. The results are documented in Table 5. The accuracy for all countries combined ranges from 51.5% (EBITFINOR) to 64.3% (NITA). The most accurate measurements across countries are for profitability (both NITA and NIOR), while in Germany, for example, their accuracy is lower than in other countries. This study compared the median results with all countries' results (see headers "RR all countries" and "Median RR" in Table 5) and observed that NITA and SFTA give the highest accuracy, while ORTA and EBITFINOR have the lowest prediction (for both T-1 and T-2). In the context of country ranks, Italy has the highest predictive accuracy, where, for example, the accuracy of SFTA and NIOR ratios is close to 75%. Hungary has also more than 70% accuracy with NITA ratios. On the other hand, for Germany and the United Kingdom, the average accuracy lags behind the other countries and is below 50% in some individual ratios: EBITFINOR for Germany and ORTA for the United Kingdom. Hungary has two indicators, namely CCLTA and ORTA, and Russia EBITFINOR, below 50%.

The most often used variables according to previous literature (Table 2) are financial ratios that characterize the profitability of a company. The failure or survival of a company is difficult to predict, it cannot be successfully done with only one single ratio (Balcaen & Ooghe, 2006). Thus, much complex use of financial ratios is needed. In Table 5 it is possible to see that across all countries the highest accuracy is achieved with profitability financial ratios. In Altman (1968, p. 597), the profitability ratio (EBIT/total assets) had the highest value in failure prediction. This can be considered logical, as a profitable company is unlikely to fail (Altman, 1968). Beaver (1966) reveals that cash flow/total debt has the best failure prediction ability (failure prediction accuracy 87%, t-1). He was the first who tried to predict the failure of a company using financial ratios in the prediction model. Pompe and Bilderbeek (2005) concluded that the same ratio (cash flow/total debt) was one of the best failure prediction ratios.

Table 5. Univariate accuracies of ratios in different countries and their ranking based on accuracies (composed by authors)

Variable	RA All countries (%)	RR All countries	RA Italy (%)	RR Italy	RA France (%)	RR France	RA Germany (%)	RR Germany	RA Hungary (%)	RR Hungary	RA UK (%)	RR UK	RA Russia (%)	RR Russia	Median RR
NITA1	64.3	1	74.3	3	64.7	2	56.1	8	71.9	1	58.3	1	63.2	1	2
NIOR1	63.8	2	74.6	2	64.3	3	55.5	10	69.8	3	57.4	4	60.4	4	4
NITA2	63.4	3	69.4	9	64.8	1	54.7	12	70.8	2	55.7	8	58.8	8	8
SFTA1	62.9	4	75.6	1	63.5	4	63.6	1	59.9	5	58.0	2	61.2	2	2
NIOR2	61.1	5	68.4	10	63.3	5	55.0	11	68.2	4	56.4	7	56.0	12	9
SFTA2	60.8	6	68.1	11	60.6	9	60.9	2	58.8	7	57.1	5	60.4	3	6
CLTA1	59.6	7	70.7	5	59.9	11	56.6	7	58.0	8	55.3	10	60.3	5	8
CACLTA1	58.3	8	71.6	4	61.3	7	57.4	5	52.6	13	55.5	9	57.8	10	8
CLTA2	58.1	9	65.0	14	58.4	12	58.1	3	57.5	9	54.5	11	59.5	7	10
CCLTA1	57.8	10	70.2	7	57.7	13	56.0	9	49.7	15	52.7	13	59.8	6	11
CACLTA2	57.2	11	66.2	12	60.2	10	57.2	6	53.3	11	54.3	12	57.1	11	11
CCLTA2	56.9	12	65.0	13	57.6	14	57.4	4	52.9	12	51.6	14	58.6	9	13
EBITFINOR1	53.4	13	59.4	15	62.8	6	48.7	16	59.4	6	57.7	3	46.9	15	11
ORTA2	52.3	14	70.3	6	55.0	16	50.3	15	52.5	14	49.0	16	50.5	14	15
ORTA1	51.9	15	69.7	8	56.2	15	51.8	14	49.0	16	51.0	15	51.2	13	15
EBITFINOR2	51.1	16	55.6	16	61.0	8	53.6	13	55.3	10	56.6	6	45.9	16	12

Note: RA – ratio accuracy, RR – ratio rank. The ratio ranks for sixteen financial ratios are notified as: “1” – the ratio with highest univariate accuracy and “16” – the ratio with lowest univariate accuracy. The “median RR” is calculated as the median rank of six country ranks. Numbers 1 and 2 in the name of financial ratios mean the last and the penultimate reports submitted.

Looking at the results of individual ratios separately for non-failed and failed companies (see Table 6 for details), we can see larger fluctuations in the accuracy of failure prediction. The most accurate are the NIOR ratios of non-failed companies, which are over 90% across countries. Also the NITA ratio values for non-failed companies show high accuracy, over 80% across countries. Within countries the most accurate results are again in Italy, where the accuracy of the individual ratios of all non-failed companies is over 66%. The non-failed companies of the United Kingdom also have values of a higher accuracy (over 60%) compared to other countries.

The lowest accuracy indicators among non-failed companies across countries are the ORTA ratio values, which in both cases are even lower than those of failed companies. Russia has the lowest score among countries used in the analysis, with the accuracies of ORTA ratios of non-failed companies around 37%. Across countries, the EBITFINOR values of failed companies yield the lowest results (29.4% and 30.3%), which can also be observed when examining the results within countries. While the NIOR values were among the highest among non-failed firms, they are among the lowest in failed firms (34.6% and 31.2%, respectively). A similar pattern can be seen for NITA. Within countries, the NIOR ratios of failed Russian companies are the least accurate, both below 30%.

Thus, when examining the accuracy of individual ratios, the accuracy of failed companies was found to be much lower than that of non-failed companies. The reason for this phenomenon, as Lukason et al. (2016) pointed out, is that financial ratios gradually deteriorate and receive poor values a year or even less before the failure. One year before failure most of the failed firms are characterized by negative profitability (NITA), very low liquidity (CCLTA, CACLTA) and an unsustainable capital structure (Lukason et al., 2016).

Beaver (1966, p. 101) found that liquid asset ratios had the weakest capability to predict failure. Many studies use cash flow-based ratios or accrual-based ratios as variables, but according to Balcaen and Ooghe (2006), it is not clear which type of financial ratios have the most predictive power, as different authors have different opinions. In all probability, it is also necessary to be critical of the financial ratios of failed or soon-to-fail companies. Companies in difficulties may embellish their financial statements (Beneish, 1999).

Table 6. Univariate accuracies of ratios in different countries and across countries of non-failed and failed firms (composed by authors)

Variable	All countries		Italy		France		Germany		Hungary		UK		Russia	
	Non-failed (%)	Failed (%)	Non-failed (%)	Failed (%)	Non-failed (%)	Failed (%)	Non-failed (%)	Failed (%)	Non-failed (%)	Failed (%)	Non-failed (%)	Failed (%)	Non-failed (%)	Failed (%)
CCLTA1	62.3	53.2	74.2	66.3	61.3	54.0	63.0	49.0	54.7	44.7	63.0	42.4	57.1	62.6
CCLTA2	59.9	54.0	65.2	64.7	59.2	56.0	61.7	53.1	56.9	48.8	60.3	42.9	54.6	62.7
CACLTA1	66.5	50.2	81.8	61.5	69.3	53.3	62.8	51.9	61.0	44.3	70.4	40.6	58.1	57.5
CACLTA2	63.0	51.4	71.0	61.5	66.6	53.8	61.5	52.8	60.2	46.4	69.3	39.3	53.9	60.4
NITA1	87.0	41.5	96.7	52.0	84.9	44.5	77.5	34.7	92.8	51.0	77.7	38.8	57.4	69.0
NITA2	81.4	45.3	92.2	46.6	81.9	47.8	73.7	35.6	84.9	56.7	73.9	37.5	45.4	72.3
NIOR1	93.0	34.6	99.0	50.2	89.8	38.8	85.8	25.2	96.2	43.3	83.0	31.7	92.2	28.5
NIOR2	90.9	31.2	97.7	39.1	87.8	38.7	80.3	29.7	95.1	41.4	84.3	28.6	89.5	22.4
SFTA1	70.2	55.7	83.1	68.1	70.2	56.8	67.0	60.2	72.1	47.6	74.6	41.5	59.3	63.0
SFTA2	65.7	56.0	67.4	68.8	66.3	54.9	63.9	57.9	69.4	48.3	73.2	41.1	54.9	65.9
CLTA1	67.6	51.5	77.4	63.9	67.7	52.1	66.1	47.2	70.6	45.5	69.1	41.5	58.2	62.4
CLTA2	64.7	51.5	68.2	61.8	65.0	51.9	65.4	50.7	68.7	46.4	68.3	40.6	55.5	63.5
ORTA1	38.5	65.3	66.4	72.9	51.4	60.9	42.7	60.8	64.8	33.3	64.1	37.9	37.2	65.3
ORTA2	40.1	64.6	69.1	71.5	50.1	59.9	40.9	59.6	38.3	66.7	58.3	39.7	37.5	63.6
EBITFINOR1	76.4	30.3	87.1	31.7	68.0	57.6	60.6	36.8	80.1	38.8	82.8	32.6	68.2	25.5
EBITFINOR2	72.9	29.4	83.0	28.2	65.4	56.5	47.9	59.3	77.8	32.8	79.3	33.9	66.6	25.1

Note: Numbers 1 and 2 in the name of financial ratios mean the last and the penultimate reports submitted.

In our empirical study we also compared the aggregate accuracies for all ratios within country and across countries, with failed and non-failed firms separately and combined. We predicted the accuracy of survival from the last report submitted before the event (T-1), the penultimate report submitted before the event (T-2), and the corresponding indicators combined. The results are described in Table 7. The most accurate predictions come from non-failed firms with T-1 and T-2 aggregates, and the poorest accuracies are generally given by T-2 failed firms, apart from the UK and Italy, where T-1 is worse. Looking at the overall results, Italy has the most accurate percentage of both live and failed firms combined, with T-1 and T-2 accounting for 83.1% and T-1 scoring 82.2%. Similarly to Italy, Hungary has higher prediction rate, with the majority of the results exceeding 70%. In the case of Hungary, performance is weaker in the T-1 and T-2 periods of failed firms, which also pulls down in the overall results (Overall %).

The logistic regression analysis by Latinen and Suvas (2013) covered 30 European countries. The best failure prediction percentage with that method in the whole sample was 71.09% (t-1). The accuracy percentage for T-1 in this work is 66.3%, which is 4.79% lower than in Latinen and Suvas (2013). In the present work, the forecasting of failed companies in the period T-1 was 6.16% better than in Latinen and Suvas (2013) (71.6% vs 65.44%).

Table 7. Aggregate accuracies for all ratios within country and across countries (composed by authors)

Country	**T-1 and T-2**			**T-1**			**T-2**		
	Non-failed (%)	**Failed (%)**	**Overall (%)**	**Non-failed (%)**	**Failed (%)**	**Overall (%)**	**Non-failed (%)**	**Failed (%)**	**Overall (%)**
All countries	77.6	56.2	66.9	76.6	56.0	66.3	72.4	54.5	63.5
Italy	91.5	74.8	83.1	92.8	71.6	82.2	83.5	73.4	78.5
France	78.7	60.3	69.5	77.8	56.8	67.3	75.1	58.0	66.5
Germany	69.8	56.1	62.9	67.6	54.3	61.0	66.1	53.7	59.9
Hungary	86.8	72.0	79.4	84.7	69.9	77.3	81.9	64.1	73.0
UK	79.7	44.2	61.9	83.4	42.4	62.9	75.9	47.8	61.8
Russia	63.1	67.2	65.2	62.5	66.6	64.5	58.3	66.8	62.5

Note: T-1 is 12 months and T-2 is 24 months before the event.

The worst results have come from the United Kingdom and Germany, where the aggregate results for all years and T-1 and T-2 taken together are close to 60%. This can be attributed to the low score of the failed firms, which ranges from 42–47% for the United Kingdom and 53–56% for Germany. For the United Kingdom, there are significant differences between the results of non-failed and failed firms, for example, with nearly double difference between the results for T-1 (failed 42.4% and non-failed 83.4%). The smallest differences in the performance of non-failed and failed companies are in Russia, where it fluctuated between 58% and 67% in all periods. One reason for that is the high accuracy for failed firms – higher in every period than for non-failed firms. Ciampi et al. (2018) found that when using only financial ratios, logistic regression results are lower than for trajectory-based models and discrete-time hazard models. Compared to our reported T-1 results, the accuracies by Ciampi et al. (2018) are significantly higher, resulting in 80.9% overall for failed and non-failed (cf. 66.3% in this work). Unlike the results of this thesis, their accuracy for non-failed companies is lower. It must be noted, however, that the failure definition in their work is different.

5. Conclusion

In this study, previous high-tech and medium-high-tech failure forecasting models were found through the literature reviews (Balcaen & Ooghe, 2006; Dimitras et al., 1996; Pretorius, 2009; Ravi Kumar & Ravi, 2007) and database searches using the relevant keywords (business failure, bankruptcy, financial distress, dissolved). Several studies (Bhattacharjee et al., 2009; Greenaway et al., 2009) have shown that voluntary liquidations can also be considered as a failure. Therefore, we included all companies in our work that have ceased operations.

This study used firm-level data from the Bureau van Dijk's Amadeus database and included the financial information of 32,929 firms. The data were collected from the financial statements of the companies for the period 2012–2017. A comparative sample of failed high-tech and medium-high-tech companies from six European countries and non-failed companies from the same countries was used. The choice of variables was based on the main financial ratios used in the previous literature, which characterize the company's liquidity, profitability, solvency and efficiency.

Our results showed that the accuracy of individual variables across countries is not very high, ranging from 51% to 64%. The most accurate ratios for all countries among failed and non-failed companies overall were NITA and NIOR, and EBITFINOR and ORTA yielded the most inaccurate results. The accuracy of the country-based forecasting models for individual variables varied more, with better results for Italy and Hungary and poorer for Germany and the United Kingdom. Looking at the results of the individual ratios separately for non-failed and failed companies, we saw larger fluctuations in the accuracy of failure prediction. The most accurate results among non-failed companies were achieved by the NIOR and NITA indicators, while among failed companies the ORTA and CCLTA indicators were more accurate.

Aggregate accuracies for all ratios within country and across countries showed that the most accurate predictions come from non-failed firms with T-1 and T-2 ratios combined, and the poorest predictions were usually from T-2 of failed firms, with the exception of the United Kingdom and Italy, where T-1 was worse. Italy and Hungary have the highest percentage of both non-failed and failed companies, with the worst results in the United Kingdom and Germany.

The practical relevance of the work stems from several aspects. From the company's point of view, it is important to know what indicators can be used to distinguish between surviving and failing companies. Knowledge of the relevant variables allows companies in a timely manner to focus on aspects that have predicted failure in the past. Financial analysts must consider that financial ratios are not the most accurate and other variables are needed to increase prediction accuracy. When making definitive conclusions it would be wise to look at the country-specific analysis. What is normal and acceptable in one country may not be the same in another.

The study can be extended in multiple ways. For future research, prediction accuracy could probably be improved by using a larger sample of European countries, machine learning, a longer time horizon, and more variables, as well as including other variables in addition to financial ratios.

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