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BANKRUPTCY PREDICTION OF EUROPEAN EXPORTING FIRMS

Bachelor Thesis

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I have written this bachelor thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

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Introduction

While the topic of bankruptcy prediction (BP) may initially appear intricate to those less familiar with financial analyses, fundamentally, it involves the evaluation of various financial indicators and risk metrics to forecast the likelihood of a company's potential bankruptcy.

The importance of bankruptcy prediction lies in its role in identifying potential financial distress within companies. By leveraging financial indicators and risk metrics, BP models serve as crucial tools for early detection of financial instability. These models estimate the probability of a company facing financial distress or bankruptcy within a specified timeframe and aid in assisting investors, regulators, and companies in making informed decisions to mitigate risks and take corrective actions. (Dimitras et al., 1996; Sun et al., 2014; Tsai et al., 2014; Laitinen et al., 2014; Altman et. al, 2016; Prusak, 2018)

As Bellovary et al. (2007) report, their history traces back to the early 20th Century, however the first notable studies appeared in the 1960's when Beaver (1966) analyzed individual ratios of several bankrupted and non-bankrupted firms in multiple sectors and their failure predictive abilities, from this research the author theorized that comparing ratios between themselves would provide a more accurate result. This led to Altman (1968) publishing the first multivariate analysis, basing itself on a discriminant analysis performed on manufacturing firms. This study has remained popular amongst bankruptcy prediction literature and to this day more and more studies have been made on the subject encompassing many different analysis methods as can be seen in Appendix A.

On one hand, one could argument that bankruptcies are needed, as they serve as a catalyst for the removal of underperforming firms, making way for the emergence of stronger, more successful companies in the market (White, 2005; Boratyńska, 2016; Prusak, 2018). But also, bankruptcy processes do not signify the end of a firm's life, but several countries offer the choice between reorganization or liquidation for firms, where reorganized companies, despite initial financial struggles, tend to showcase improved performance and asset management post-revival (Zhang, 2010; Yang et al., 2015; White, 2005).

On the other hand, these failures should be limited as they may have detrimental effects on several strands of society, as it has been seen in the cases of Enron in 2001, Parmalat in 2003 and, most notably, Lehman Brothers in 2008, which had rippling effects all over the world. These events can significantly impact various stakeholders such as owners, shareholders, employees, and creditors, resulting in the loss of employment, savings, investments, and both movable and immovable assets. Additionally, they can lead to pension losses on top of other financial impacts, which not only affect individuals but also contributes to reduced tax revenues and the destruction of regions (Boratyńska, 2016). According to Chava et al. (2022) bankruptcies of local firms can significantly affect their respective counties, escalating municipal debt costs, amplifying financial strains, and inducing to economic adversity, leading to a consequential decline in GDP growth within impacted counties.

Furthermore, corporate bankruptcy impacts the entire supply chain, influencing the decisions and performance of other involved parties and companies (Battiston et al. 2007). For example, suppliers might lose a big source of profits or fear loss of sales, offer concessions before and after bankruptcy, redistributing costs by benefiting the distressed firm while harming themselves. (Yang et al., 2015)

In the recent global landscape, exporting firms face significant challenges due to increased competition. Globalization has removed many trade barriers, creating an environment where these companies must work harder to maintain their market positions. With more alternatives available and an influx of competitors, firms find it difficult to adapt quickly to changing market demands and as a result, many struggle to keep up, leading to a higher risk of financial instability which often leads them to exit foreign markets (Sousa & Tan, 2015).

What has changed in today's world is that one company is not competing against its surroundings anymore, but with the whole globe. The playing field has expanded and so has the pressure on exporting firms, especially when compared to their counterparts from third world countries, which may produce even cheaper products in terms of both manufacturing expenses and their shipping costs relatively to the exporting firms' products. On top of that Eduardsen & Marinova (2020) argue that in addition to operational challenges, firms who engage in International business have to incur into other forms of risks, which can be classified into political, country-specific, foreign exchange and cultural risks. As a result, appropriate bankruptcy prediction models should be developed to address the current economic landscape for exporting firms.

However, the literature has not been extensive on this particular sub-field, according to Nummela et al. (2014) scholars haven't fully grasped the dynamics of failure in internationalization, moreover as Lukason & Vissak (2017, p. 1) point out that "some areas of failure research – especially, firm failure processes in the international business context – have not received sufficient research attention" and to the author's knowledge, so far there are only another few studies which regard the failure field and especially bankruptcy prediction for exporting firms.

The aim of this thesis is to construct single-year and multi-year bankruptcy prediction models for European exporting firms. These models aim to combine financial indicators, firms' characteristics, and data from exporting information, to see their relationships and relative significance, but, most importantly, enable an accurate forecast of potential bankruptcy among European companies involved in international trade.

The author has outlined the following research tasks, which are essential to achieve the aim of the thesis:

- to outline the stages and factors contributing to firm failure;
- to give an overview regarding earlier bankruptcy prediction studies and assess the evolution of predictive tools and failure indicators;
- to analyze the studies of European exporters in the literature in regard to the failure field;
- to code financial and non-financial variables of European bankrupted and healthy exporting firms into an appropriate database which can be analyzed;
- to compose different bankruptcy prediction models utilizing a series of predictive tools;
- to compare and discuss the results which emerged from the analysis of BP models.

The first chapter will be comprised of three subchapters, in which the first will give a theoretical overview of key terms related to the topic, the process which leads to firms' failure, through its stages, different patterns, and the final consequences. Following, in the second there will be a comprehensive overview of bankruptcy prediction studies, which variables and predictive tools are chosen and, finally, the third will provide an analysis of literature on European exporting firms' failure.

The second chapter will be comprised of two subchapters, the first will give an overview into the coding of the database and the methodology for the analysis, explaining the composition of the models. While the second will showcase the results derived from the interpretations of the models.

Keywords: bankruptcy prediction, firm failure, exporting firms

1. Firm Failure and its Prediction

1.1 Firm Failure Process

Previously, the author introduced terms such as 'insolvency,' 'bankruptcy,' and 'firm failure,' using them interchangeably, this, however, might lead to confusion for the reader. The ambiguity arises from the lack of consensus among scholars in failure prediction studies, as there is no singular definition of failure (Boratyńska, 2016; Shi & Li, 2019). Some works even omit providing a concrete definition (Bellovary et al., 2007). Therefore, before delving into the firm failure processes (FFPs), brief overview will be made, outlining some of the various interpretations of failure according to the literature and how it will be dealt with it in this study.

Scholars differ in their definitions, some strictly view it as insolvency (Altman and Hotchkiss, 2005), bankruptcy or liquidation, while others encompass broader financial strain or the inability to meet commitments (Bellovary et al., 2007). In essence, as indicated by Beaver (1966), Dimitras et al. (1996) and Shi & Li (2019), failure represents a state where a company cannot meet obligations to lenders, shareholders, or suppliers, leading to operational disruptions.

Moreover, Goudie & Meeks (1991) propose four broad categories that potentially classify a firm as failing. Although severe financial distress doesn't always culminate in bankruptcy, the authors argue that these certain scenarios might signify failure:

A. Liquidation or receivership (or filing under chapter 7 or 11 in the US);
B. Takeover;
C. Liquidation of a subsidiary of the parent company;
D. Possible failure prevented by a rescue package, possibly funded by the government, bankers, or related creditors.

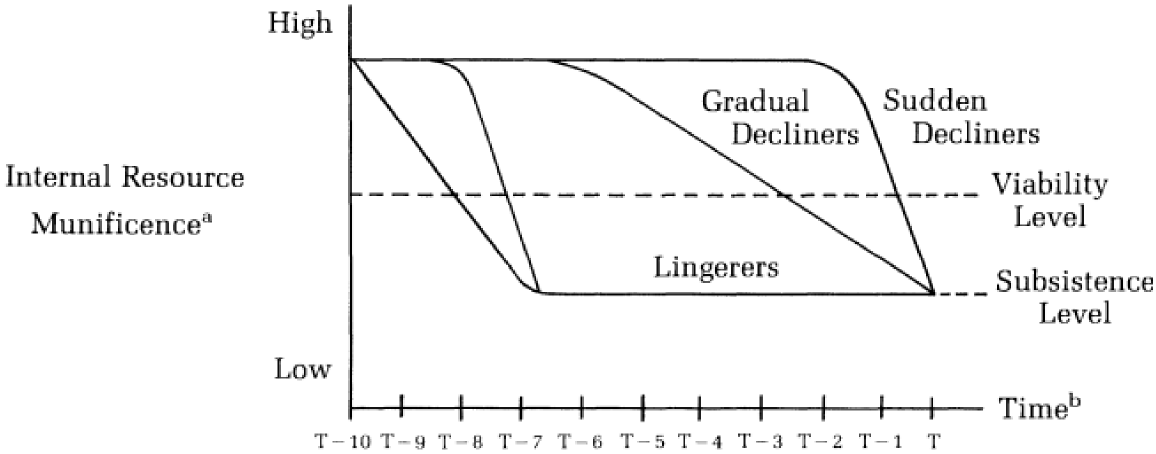
Nonetheless, despite varying perspectives, scholars generally base prediction models on corporate bankruptcy as the core indication of failure (Altman and Hotchkiss, 2005; Bellovary et al., 2007; Shi & Li, 2019; Lukason & Laitinen, 2019), therefore the author will do so as well. Moreover, bankruptcy provides a clear indication of a firm’s failure, since it expresses the moment in which a company would like for operations to cease due to their inabilities to meet financial obligations, unlike other forms such as “in liquidation” which describes the process of dismantling and may or may not, necessarily, happen because of failure. Additionally, while acknowledging the distinct definitions of terms like bankruptcy and insolvency, they are often considered synonymous in the literature (Boratyńska, 2016), hence, for ease, these words will be treated as synonyms of bankruptcy.

However, it is important to recognize that corporate bankruptcy represents merely the conclusive stage of a complicated progression. Before a firm goes through the formal declaration of bankruptcy, it passes through a sequence of discernible stages, each indicating varying degrees of financial distress and operational instability. Starting with subtle precursors, initial indicators manifest as operational inefficiencies or financial discrepancies within the organizational framework. A period of decline follows, showing a gradual decrease in the availability of internal resources as time goes on (Cameron, Sutton, & Whetten, 1988). D'Aveni (1989) expands on this by indicating the measurements of decrease:

- Financial resources, which decline when liquidity, profitability, and borrowing capacity decrease due to higher leverage. These resources are vital for investments and to handle short-term cash crises.
- Managerial resources, which decline when there's a reduction in prestigious top managers, affecting a firm's human capital. Top managers' education, status, and prestige lend legitimacy to a firm among external stakeholders, ensuring access to essential resources from exchange partners.

As financial and operational challenges persist, these company's resources deplete, which can lead to increased vulnerability. This downward spiral may cause a company to declare bankruptcy, triggering legal proceedings where the firm in question will try to settle its debts.

Nonetheless, the concept of firm failure processes is a dynamic phenomenon that varies significantly. Argenti (1976) was the first conceptualize different kinds of failure in the literature through a theoretical framework. The author conceived three types of firms, the first type would experience a low performance which never improved, the second type would have a sharp rise followed by a progressive crash and the third would undergo a sudden collapse after a period of excellent performance. Basing itself on Argenti's (1976) initial idea, D'Aveni (1989) proved the existence of these processes by tracking how firms' vital resources decreased over time, the specific variables on which the study focused were equity-to-debt ratio and managerial reputation. As a result, three decline processes were identified – sudden decline, gradual decline, and lingering. As D'Aveni (1989) illustrates in figure 1, firms may go through a sudden decline involving swift collapses typically within a year from bankruptcy. In contrast, gradual decline includes a slower descent culminating in bankruptcy which take places in the span of two to three years, while lingerers struggled several years before declaring bankruptcy.



[a] The index of internal resource munificence reflected both financial and managerial resources.
[b] T = year of bankruptcy; T − 1 = the year preceding bankruptcy, and so forth.

Figure 1. Proposed Patterns of Declining Resources Preceding Bankruptcy
Source: D'Aveni (1989)

Following D'Aveni's (1989) breakthrough work, Laitinen (1991) conducted a similar research focusing on financial variables and using a dataset of Finnish firms. This study confirmed the existence of three main typologies of failure processes, similarly to Argenti's (1976) initial idea, and categorized them as "chronic failure firms", "revenue financing failure firms", and "acute failure firms". But most importantly, when comparing D'Aveni's (1989) and Laitinen's (1991) works, noticeable differences can be identified in the share of processes amongst American and Finnish firms. Also, Laitinen (1991) theorized that the size, industry type, and failure pattern of a company are linked, and these factors are important for predicting when a company might fail and how failure process are influenced. As a result of this study a question emerged in the firm failure literature, questioning what are the components that influence failure processes.

Since Laitinen's (1991) work, the field has expanded, contributing to a deeper understanding of firm failure processes. The result of this is the emergence of several unique studies each with their own particularities, for example authors have been encompassing different approaches, either qualitative (Argenti, 1976; Ooghe & De Prijcker, 2008), quantitative (D'Aveni, 1989, Laitinen, 1991; Laitinen & Lukason, 2014; Lukason et al., 2016; Laitinen et al., 2014; Lukason & Vissak, 2017; Lukason & Laitinen, 2019; Lukason, 2018), but also hybrid (Makropoulos et al., 2020), offering varied insights into the dynamics of FFPs. Moreover, some of the most important findings in the literature is the existence of different number of processes, which go from 2 (Lukason et. al, 2016; Lukason & Laitinen, 2016), 3 (Argenti, 1976; D'Aveni, 1989; Laitinen, 1991; Lukason & Vissak, 2017; Lukason & Laitinen, 2019; Lukason, 2018), 4 (Ooghe & De Prijcker, 2008; Lukason et. al, 2016; Laitinen et al., 2014; Makropoulos et al., 2020) to 5 or 6 (Laitinen & Lukason, 2017). According to Lukason & Laitinen (2019, p.1) "the existence of different FFPs is by now a well-established fact and there is enough evidence how FFPs differ in respect to financial situation evolvement in time."

These differences can be attributed all sorts of factors affecting the way and how companies fail, for example the existence of different firm failure processes extends across diverse geographical and socio-economic contexts. For instance, Lukason & Laitinen (2016) discovered notable interregional disparities in FFPs, particularly between countries with initial capitalist backgrounds and those formerly under socialist regimes. This suggests that historical economic characteristics can significantly influence the dynamics of firm failures. Moreover, Laitinen et al. (2014) shed light on distinct FFPs between Eastern and Western European countries. This discrepancy may stem from legislative variations, with Western European nations benefitting from more standardized regulatory frameworks within the European Union (EU), while Eastern European counterparts may face legislative gaps or discrepancies owing to recent EU integration or non-membership status. Moreover, as Laitinen & Lukason (2014, p.19) argue that "although laws are similar in two countries analysed, their implementation can vary", which could raise an argument as to how legislation is enforced for possible failure processes. Another case can be made for the level of development of a country and as Lukason & Laitinen (2019) observed differing patterns of firm failure between developed and developing economies, with the former characterized by abrupt failures which could be facilitated by robust insolvency legislation, while the latter often experience prolonged failure processes due to deficiencies in legal enforcement and market mechanisms.

The size of a company may play a role in shaping its failure processes, as evidenced by Lukason & Laitinen (2016), who observed certain distinct trends among firms of varying sizes. Their study revealed a tendency for various sized enterprises to exhibit different failure processes. However, the strength of these associations remains uncertain, as the evidence presented by Lukason & Laitinen (2016) is deemed weak and inconclusive. However, Lukason (2018) noted that as companies become bigger, the gradual failure process becomes more common, hence a relationship can be noted. Furthermore, age also emerges as a significant factor influencing firm failure processes, as highlighted by Lukason et al. (2016). Their study revealed that the older a company get the less FFPs exists, however it's important to note that this observation was made within the context of relatively young companies, with analysis conducted on firms ranging from three to six years old. But as previously mentioned from Lukason (2018), as a company gets larger, gradual failure becomes more likely as the pattern of failure. This may indicate a stabilization of larger companies into more static failure patterns, which is also supported by the fact that these firms are less likely to be affected by external shocks unlike small and medium enterprises (SMEs).

Additionally, the industry in which a company operates can significantly influence its failure processes, as noted by Laitinen et al. (2014) although the evidence being weak, the authors observed a particular failure process to be more prevalent within a specific industry group, suggesting a potential correlation between industry characteristics and failure patterns.

One important factor that should not be overlooked at are sample characteristics and how they can shape firm failure processes as described by Laitinen (1991, p.19), who emphasizes that "there is a dependence between the size, business branch, and the type of failure process. Hence the characteristics of the sample play a central role in failure prediction."

D'Aveni (1989) emphasizes that bankruptcy frequently arises from ventures into high-risk actions, such as expensive acquisitions or sudden shifts in strategic direction. These tendencies are particularly pronounced in stagnant organizational structures or firms lacking clear direction. Additionally, D'Aveni (1989) introduces the concept of "lingering," which describes the adoption of survival tactics following a decline. These tactics often entail downsizing operations to delay the inevitability of bankruptcy, although they are typically accompanied by significant financial and managerial challenges. Moreover, Ooghe & De Prijcker (2008) pointed to various internal and external factors contributing to bankruptcy, including managerial incompetence, lack of experience, authoritarian leadership, over-optimism, incorrect turnover estimations, external shocks, insufficient training, and a mistrust of customers. Also, it could be argued that bankruptcy is not solely attributable to the decline of the firms but as it can be attributed to companies' inability to match their pace of growth (Ooghe & De Prijcker, 2008; Laitinen and Lukason, 2014; Laitinen et al., 2014).

Regardless of the differences discussed, there exists some commonalities for firm failure processes, for example Argenti's (1976) original framework for three distinct types of decline patterns remains significant, as similarities can be traced to D'Aveni (1989) and can be seen in Figure 1, also Laitinen (1991), and Laitinen et al. (2014) have delved into various dimensions of FFPs, with their findings often intersecting with Argenti's typologies. Moreover, works such as Lukason & Laitinen (2016) and Lukason (2018) have utilized this framework as a benchmark for categorizing firm failures, further affirming its enduring relevance in the field. While within the spectrum of identified FFPs, gradual decline emerges as the most prevalent, as suggested by Lukason (2018). This observation is particularly pronounced in larger firms, where the detected gradual failure process becomes more frequent (Lukason et al., 2016, Lukason & Laitinen, 2016; Lukason, 2017; Lukason & Vissak, 2017; Lukason, 2018).

Overall, the analysis of firm failure processes can be a very important process in constructing effective bankruptcy prediction models, since understanding firm failure guides the strategic selection of variables as the context of failure is clearer. This, as a consequence, facilitates the development of robust models and makes it so that a more accurate forecasting of financial difficulties or bankruptcy can be performed. For example, Laitinen (1991) suggests adapting financial ratio usage to accommodate these differences. Studies by Laitinen & Lukason (2014) and Laitinen et al. (2014) highlight country-specific disparities in bankruptcy triggers. For instance, Lukason et al. (2016) find that in less developed economies, liquidity crises often precede bankruptcy, while in more developed ones, profitability crises and mismanagement are more common, but also forecasting bankruptcy becomes more challenging for young firms, suggesting the need for additional non-financial information to be analysed alongside classical indicators. Lukason & Laitinen (2016) note consistent declines in profitability, capital structure, and liquidity ratios preceding collapse. Lukason (2018) emphasizes monitoring profitability and cash flow creation, especially for large firms. Lukason & Laitinen (2019) suggest integrating non-financial variables in SME prediction models to enhance accuracy, particularly for short-term failure. Incorporating market-specific variables could further improve predictions.

If future studies successfully capture and effectively account for these critical differences, they could pave the way for the development of highly effective bankruptcy prediction models. These models would possess the capability to forecast failures despite the diverse nature of companies and their unique situations. This highlights the understanding that companies of different types and various industries, could fail in unique ways and it emphasizes the importance of crafting bankruptcy prediction models that are made for specific contexts.

1.2 Bankruptcy Prediction Literature

Over the past nine decades, bankruptcy prediction has evolved into a prominent subject within finance, attracting extensive research attention and producing notable advancements. This progression can be delineated into distinct eras, each characterized by unique methodologies and breakthroughs.

The first “era” began in the early 20th century, focused primarily on univariate analysis of financial ratios. As Bellovary et al. (2007) report, several studies were conducted during this period, and several key ratios were identified, including working capital to total assets, surplus and reserves to total assets, net worth to fixed assets, fixed assets to total assets, the current ratio, net worth to total assets, sales to total assets, cash to total assets, net worth to debt, net profits to net worth, debt-to-worth ratios, and liquidity measures. These findings gave some initial insights into the significance of specific variables to forecast failure and laid the foundation for the evolution of bankruptcy prediction.

However, as mentioned in the beginning of the thesis, the first significant breakthroughs made in the field of bankruptcy prediction models appeared in the 1960’s when Beaver (1966) conducted a univariate analysis. In his study the author explored the predictive ability of a set of 30 financial ratios amongst both failed and non-failed firms across various industries to analyse their significance in forecasting a company's failure. In his findings Beaver (1966) noted 6 significant ratios being: cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current ratio, and no-credit interval. Most importantly, the author advanced the notion that a more precise assessment could be achieved by comparing these ratios against each other.

Because of his suggestion, Beaver (1966) led the way to the beginning of the second “era”, which saw the emergence of multivariate analysis being implemented in the creation of prediction models based on the author’s suggestions. The most important study in the field of BP was performed by Altman (1968) publishing the first multivariate discriminant analysis (MDA). As Bellovary et al. (2007) reports, Since Altman (1968) published his MDA study, the bankruptcy prediction field rapidly became a mainstream academic field and more than 100 studies were written until the turn of the century, also as can be seen in Appendix A several different methods have emerged as possible substitute to be implemented instead of multi discriminant analysis in the creation of BP models. Nonetheless it’s crucial to note that these are only some of the many methods in existence. As the field of failure prediction skyrocketed, it became more and more studied as the years passed, however due to the limitations of this work the author will concentrate on Altman (1968) and some of most relevant studies made after it.

Returning to Altman's (1968) study, the author analyzed a group of 66 manufacturing companies, half of which failed and the other not, and built the following model:

$$Z = 0.012X_1 + 0.014X_2 + 0.0033X_3 + 0.006X_4 + 0.999X_5 \qquad (1)$$

Testing 22 popular financial ratios, the results showed Working Capital/Total Assets (X_1), Retained Earnings/Total Assets (X_2), Earnings before Interest and Taxes/Total Assets (X_3), Market Value of Equity/Book Value of Total Liabilities (X_4), Sales/Total Assets (X_5) in being good indicators for possible failure. Altman (1968) classified 3 separate zones, where the result of the firm, called Z-score, would fall into. The safe zone being above the value 2.99, the red zone being below 1.81, and furthermore a grey zone between 1.81 and 2.99 where result differed providing a moderate chance of failure. The study provided high accuracy of bankruptcy predictability for t-1 period, although the accuracy of the model noticeably decreased the more years before the t year, which is the period when firms declared bankruptcy. Altman's (1968) model has stood the test of time and is considered a cornerstone of bankruptcy prediction as it offered a tool to measure financial health, furthermore thanks to the work of Altman et al. (2017), the original Z-score was tweaked, as the original was only suited for publicly traded companies, and adapted for private firms by substituting Book value of equity/Book value of total liabilities at X_4:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \qquad (2)$$

Moreover, after some reconsiderations and changes made like the exclusion of Sales/Total Assets (X_5), the author recreated an improved 4 variable Z-Score model that could be employed for either public or private firms:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \qquad (3)$$

Altman et al. (2017) conducted a comprehensive international study to evaluate the effectiveness of accounting-based Z-Score models in predicting bankruptcy or financial distress across various countries. The authors analysed a sample of around 3 million SME firms of both operating and failed, which included also public, but predominantly private companies, from 31 European countries, China, Colombia, and the United States. As it included both public and private firms, Altman et al. (2017) utilised the updated Z-Score (Equation 3) and found that the model performs well with international datasets, however, the authors note that by adding additional variables to this model, better results can be found, and similarly at a country specific level it can be improved by adding relevant national variables. Moreover, the authors highlight a significant insight regarding SMEs: Altman et al. (2017) found that enhancing model accuracy through the inclusion of additional variables, particularly focusing on size, is beneficial. However, they also observed that as companies decrease in size, their financial ratios tend to become more unstable and erratic in failure prediction. While the authors addressed this challenge by setting limits on the firms studied, there's an opportunity to create specialized models that account for SME instability by incorporating potentially relevant additional variables.

As discussed previously, one of the most important aspects in the creation of a bankruptcy prediction model is the choice of variables. Aside from the indicators highlighted in the early era, Beaver (1966) emphasized ratios such as cash flow to total debt, net income to total assets, and working capital to total assets, while Altman (1968), on the other hand, refined the selection process by incorporating variables like retained earnings to total assets and market value of equity to book value of total liabilities, derived from both theoretical considerations and empirical evidence. Finally, Altman revised the original Z-score model to suit privately held firms, adapting it by substituting Book value of equity/Book value of total liabilities, thus expanding its applicability (Altman et al, 2017).

By having knowledge about the significance of variables in predicting failure, such as the ones from before, it enables to get an advantage in the creation of a bankruptcy prediction model. However, when designing such framework, the selection of variables is crucial as some situations might require different needs, some prioritize liquidity measures while others might need a focus on profitability indicators or leverage ratios. Therefore, during the modelling process, in order to get a strong accuracy, the selection must be done appropriately, drawing from past research and theory while also accounting for the unique characteristics of the firms and industries under investigation (Du Jardin, 2009).

Building on the understanding of the importance of variables in predicting failure, it becomes evident that financial variables are a good tool to forecast firms' instability due to their ability to encapsulate various aspects of a firm's financial health and performance, in fact as Dimitras et al. (1996, p.2) state "Financial ratios were introduced early as characteristics able to predict the failure of a firm." Furthermore Du Jardin (2009, p.8) tells how "there is a huge number of ratios that have proven to have good predictive ability " and "that in the last forty years more than 500 different ratios have been used to build modes."

Over the course of the literature, numerous financial variables have demonstrated their significance in predicting bankruptcy. These variables have been extensively studied and incorporated into various models, contributing to the development of robust bankruptcy prediction frameworks. In table 1 there are indicated some of the most used variables in the literature, however, all possess different characteristics and are suitable for specific measures.

Table 1

Factors Included In Multiple Studies

Factor/Consideration	Number of Studies Included in
Net income / Total assets	54
Current ratio (Current Assets/Current Liabilities)	51
Working capital/Total assets	45
Retained earnings / Total assets	42
Earnings before interest and taxes / Total assets	35
Sales / Total assets	32
Quick ratio ([Cash and Equivalents + Accounts Receivable] / Current Liabilities)	30
Total debt / Total assets	27
Current assets / Total assets	26
Net income / Net worth	23
Total liabilities / Total assets	19
Cash / Total assets	18
Market value of equity / Book value of total debt	16
Cash flow from operations / Total assets	15
Cash flow from operations / Total liabilities	14
Current liabilities / Total assets	13
Cash flow from operations / Total debt	12
Quick assets / Total assets	11
Current assets / Sales	10
Earnings before interest and taxes / Interest	10
Inventory / Sales	10
Operating income / Total assets	10

Notes. Only variables appearing 10 times, or more were kept from the original table

Source: Compiled by the author from Bellovary's et al. (2007) Appendix A

For instance, the net income divided by total assets ratio provides insights into a firm's profitability relative to its overall asset base. Similarly, the current ratio, which is calculated by dividing current assets by current liabilities, offers a measure of a firm's short-term liquidity and its ability to cover immediate financial obligations. Additionally, the quick ratio, derived from dividing the sum of cash and equivalents plus accounts receivable by current liabilities, provides further insights into short-term liquidity. Furthermore, the total debt to total assets ratio sheds light on a firm's overall leverage, indicating the proportion of assets financed by debt. Meanwhile, the cash flow from operations divided by total assets ratio demonstrates the efficiency of a firm in generating cash relative to its asset base.

When developing a bankruptcy prediction model, it's crucial to carefully consider its intended purpose and select the variables accordingly to construct a more effective framework, however Du Jardin (2009, 2012) reports that across a great majority of the literature, the selection criteria for Indicators is based simply on their popularity. Having stated this, there is no denial that there are variables which have strong bankruptcy prediction power, however Du Jardin (2009, p.11) further states that “there is no guarantee that variables that have proven reliable bankruptcy indicators in some circumstances will always be so in others”, so “it is always better to seek ad hoc variables.”

Furthermore, the literature shows that there is a definite bias towards financial ratios as they have shown to be valuable indicators for assessing a company's performance under normal circumstances. However, they may fall short in predicting failure during challenging economic conditions or sudden environmental changes caused by external shocks (Dimitras et al, 1996). To enhance predictive accuracy, researchers could consider additional aspects beyond financial metrics, which may stem from either qualitative or quantitative characteristics of firms other than accounting ones (Du Jardin, 2009). Factors such as management quality, personnel, product offerings, and equipment can significantly influence a company's performance and future prospects. Moreover, when predicting the failure of firms within specific sectors, it becomes crucial to consider sector-specific characteristics. (Dimitras et al, 1996; Du Jardin, 2009) Especially because, as Dimitras et al. (1996) notes, it has been observed that financial ratios do not exhibit a normal distribution, which may compromise the effectiveness of traditional statistical methods in bankruptcy prediction models. Therefore, a holistic approach that incorporates both financial and non-financial factors may perform well and provide robust predictive modelling.

In the process of developing robust bankruptcy prediction models, the choice of analytical tools represents another fundamental aspect, in fact according to Alaka et al. (2018, p.1) “the performance of such models is largely dependent on, among other factors, the choice of tool selected to build it.” These methods in question encompass a broad spectrum of methodologies, ranging from traditional statistical techniques to advanced machine learning algorithms. Over the years, there has been a notable expansion in the variety of analysis methods utilized. As Du Jardin (2009) highlights, more than fifty distinct methods can be seen across the literature now. Appendix A showcases some of the most utilized and dependable methods in this regard. Different tools employ distinct strategies, allowing analysts to explore various aspects of a company’s health and uncover patterns that may not be apparent using one single method. Moreover, the tools have also been employed together instead of only being used by themselves (Dimitras et al., 1996), often creating even better performing models (Tsai et al., 2014).

When choosing which tool may be more appropriate for the creation of the model, there is a criteria which should be considered, in table 2 are listed 13 criteria which Alaka et al. (2018) identifies to be the most important.

Table 2

BP models tool choice criteria

Criterion	Description
Accuracy	How often a tool correctly predicts bankruptcy
Result Transparency	Interpretability of a tool's result
Non-Deterministic	How well the tool can be applied on different companies other than the ones tested on
Sample Size	Optimal size of a sample needed for a tool to work well
Data Dispersion	How well a tool handles different data distributions
Variable Selection	How well variables are chosen
Multicollinearity	Sensitivity of the tool to multicollinearity
Variable Types	Capability to analyse quantitative/qualitative variables
Variable Relationship	Tool's limitation in analysing linear or non-linear variables
Assumptions imposed by Tools	Requirements a sample data has to satisfy for a tool to perform optimally
Sample Specificity/Overfitting	Degree of performance in regard to sample training firms but badly on validation data
Updatability	How easy it is to update a tool's model with new data
Integration Capability	How easily different tools can be combined

Source: Compiled by the author from Alaka et al. (2018)

According to the authors, while a financier or client may prioritize the accuracy of the model, focusing on its ability to determine whether a firm is financially viable enough to be granted a loan or contract, a firm owner may value result transparency equally to accuracy. The latter seeks to understand where and what aspects of the firm are in jeopardy, directing rescue efforts accordingly. In this scenario, a tool that offers both high accuracy and result transparency becomes crucial for building the required BPM. However, three key dimensions which can be outlined from table 2 are:

- Accuracy – as it directly reflects a model's predictive power;
- The non-deterministic aspect – as it emphasizes the usability of a model on companies outside of the tested ones;
- Result transparency – as it ensures the clarity and understandability of the model's outputs.

These dimensions can provide enough basic information for evaluating and selecting the most suitable predictive modelling tool for most specific applications. According to Tsai et al. (2014) and Alaka et al. (2018) in terms of accuracy machine learning techniques such as artificial neural networks (NN or ANN), especially, support vector machines (SVM) and generic algorithms (GA) constantly outperform conventional statistical methods like logistic regression (LR) and MDA. Generally, AI tools are more accurate than statistical tools, however this is not the case for all. Decision Trees (DT) have been classified as a somewhat weaker classifier, slightly better than LR. While lastly, rough sets (RS), followed by case-based reasoning (CBR) have been found to be, overall, the least accurate tools amongst the tools mentioned in Appendix A. Furthermore, GA, although relatively accurate, is more suited for the variable selection process (Alaka et al., 2018). Therefore, combining GA for variable selection and another tool such as ANN to develop BP models would be more appropriate, also because as Alaka et al. (2018, p.16) state "AI tools are more flexible and allow integration with other tools better than statistical tools do."

Another important dimension outlined by Alaka et al. (2018) is the presence of non-deterministic outcomes for predictive tools, this dimension represents the extent to which these tools can be effectively applied to companies beyond those initially tested. Since certain tools cannot perform these functions well, it can substantially hinder accuracy by leading to two types of errors. Type I error occurs when a predictive tool mistakenly labels a financially troubled firm as healthy, while Type II error involves misclassifying a stable firm as distressed. Although reducing Type I error is more crucial, mitigating Type II error is also important for financial stability. Alaka et al. (2018) found that the errors follow similar patterns to the accuracies, with ANN and SVM possessing the least number of errors, followed by GA, and DT and LR being around the same. Lastly, MDA appears to be the poorest, while CBR and RS did not have sufficient observations.

Regarding result transparency, according to Alaka et al. (2018), the accuracy of ANN and SVM are obscured by their "black box nature", which makes it challenging to understand their inner workings and interpret their results. On the other hand, AI tools like RS, CBR, GA, and DT generate decision rules that are more easily interpretable. However, GA may occasionally produce unclear or inconsistent rules, leading to difficulties in applying the model to real-world data. Alak et al. (2018) also note that among statistical methods, LR provides transparent results, with coefficients indicating the importance of variables, facilitating the identification of key areas of concern in failing firms. However, other statistical tools like MDA may produce seemingly interpretable results, but their coefficients do not accurately represent variable importance, leading to difficulties in interpretation, and occasionally resulting in counterintuitive model outcomes. Moreover, as can be seen in Appendix A, there are many more characteristics to predictive tools. For instance, Logistic

Regression and AI tools excel in identifying nonlinear relationships, while Multiple Discriminant Analysis (MDA) is limited to linear relationships, and Case-Based Reasoning (CBR) may struggle with small sample sizes. Moreover, although, most predictive tools are susceptible to data changes over time, LR and RS are much more significantly affected than their counterparts.

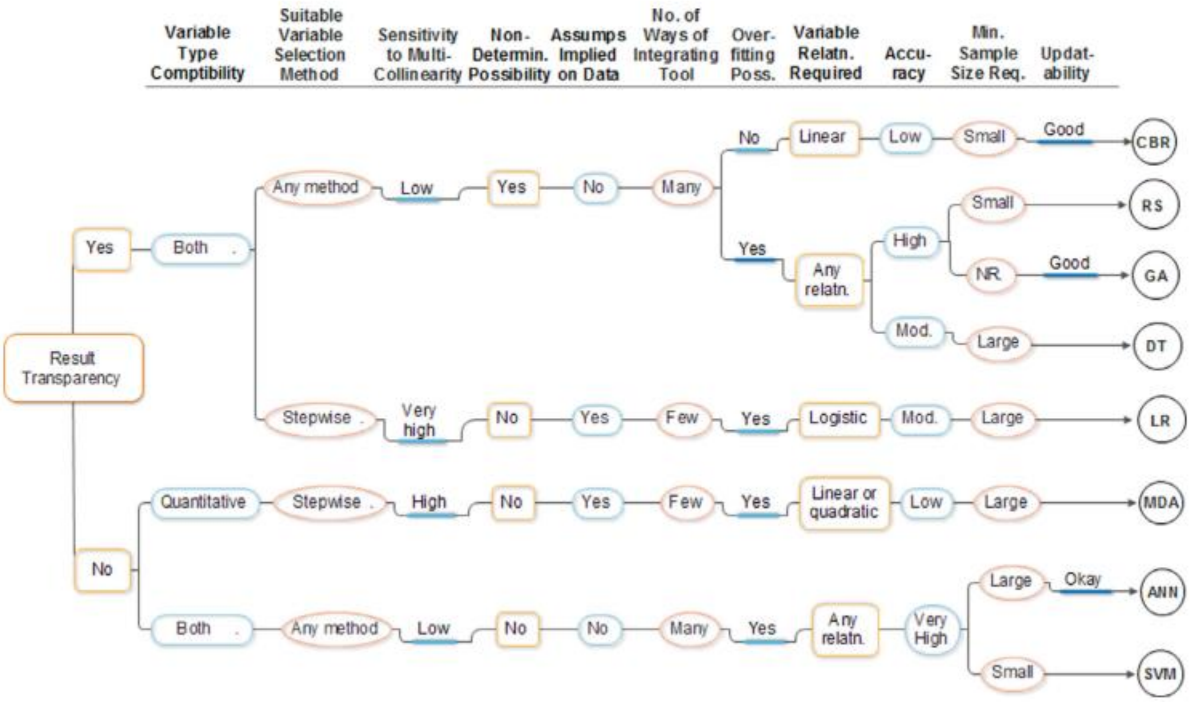


Figure 2. A framework for selection of the most suitable tools for various situations. Source: Alaka et al. (2018)

Understanding the nuances of each tool's characteristics is vital for selecting the most suitable approach for developing the best predictive model. Basing themselves on the dimensions outlined in table 2, Alaka et al. (2018) developed a step-by-step framework which can be seen in figure 2. Stakeholders are initially asked to assess the importance of interpretability, considering whether the model's results need to be easily understandable and explainable. Following this, the framework addresses whether researchers require that the tool is capable to handle both quantitative and qualitative variables and how variable are chosen, either through a stepwise methods or any other way. Next, the framework examines the tool's sensitivity to multicollinearity, which refers to whether the independent variables analysed in the predictive model maybe a high correlation between each other unlike with the output variable. Sample data requirements are then identified, considering factors such as data quality, representativeness, and sufficiency for reliable predictions. The ease of combining different tools or techniques to improve predictive performance is also assessed, along with the model's performance on both training and validation data to avoid overfitting, or in another word the capability of testing data aside from the training one. Furthermore, the framework addresses the tool's capability to handle linear and non-linear relationships between variables. The accuracy of the model in predicting is then evaluated, along with considerations of sample size for reliable predictions and, lastly, model creators assess the ease of updating the model with new data or incorporating changes over time, ensuring its relevance and effectiveness in dynamic environments. By systematically evaluating these dimensions, whoever is creating predictive models can make informed decisions, selecting predictive models that best align with their objectives and constraints. This structured approach enhances the likelihood of achieving accurate and actionable predictions in various domains.

1.3 Studies on Exporters' Failure

So far into the thesis the mentioning of the exporting sector and exporting firms has been relatively minimal, this has to do lack of information on this topic, therefore in this subchapter the relation of the previous literature to exporting firms will be covered.

To begin, the definition of failure in the context of exporting businesses, similarly to the ambiguity surrounding the general concept of failure for firms, remains fluid and lacks a universally agreed-upon framework. Diverse perspectives have been provided by scholars in the Internationalization field, from one side Benito and Welch (1997) assert that failure in exporting can be indicated through the process of de-internationalization, involving voluntary or forced actions leading to a reduction in a company's multinational engagement, potentially culminating in complete withdrawal. Francioni et al. (2017) also noted how failed internationalization could be viewed as failed entry attempts or partial and complete exits from one or more markets. However, Pauwels and Matthyssens (1999) differentiated between forced and strategic withdrawals, emphasizing that a strategic withdrawal should not be indicative of failure, as it may result from internal factors like new strategic goals or external factors such as a continuously shifting business environment. In a similar manner, Nummela et al. (2014) note that failure could be classified as significantly unexpected reduction in international business being made.

On the other side, several studies argue that for internationalization exits from market should not be considered as failure, as within business practices, market turnover fluctuations are frequent, and strategic considerations may justify complete de-internationalization in specific circumstances, (Crick, 2003; Trapczynski, 2016; Vissak & Francioni, 2013).

Moreover, companies may choose to exit due to adverse external factors like government regulations or macroeconomic uncertainty (Belderbos and Zou, 2009; Soule et al., 2013).

It's important to note that there are differences in exporters, as many different companies will have different shares of export, for this reason Lukason & Vissak (2017) classifies them into three types:

1. Experimental Exporters: Firms engage in limited, sporadic export activities, often in response to unsolicited orders or exploring nearby markets.
2. Committed Exporters: These firms have a significant involvement in exporting, with a substantial share of their business dedicated to international markets. Managers actively seek and pursue international orders.
3. Active Exporters: Positioned between experimental and committed exporters, this group shows varying degrees of commitment and engagement in international trade, with export shares not explicitly defined.

This differentiation is important as different types of exporters might fail in different ways. Although the literature is small, failure processes have been tested for exporting firms as well. However, Lukason et al. (2016) and Lukason & Laitinen (2016), although not focusing directly on exporting firms, reported that processes for exporters did not differ significantly between both old and young companies.

However, Lukason & Vissak (2017) were able to identify three types of failures. The authors conducted factor and cluster analyses of six financial variables from Laitinen's (1991) model on a sample of French 131 bankrupted exporters. The results concluded that 79% were made up by two processes which observed similarities with Laitinen's (1991) gradual decline. According to Lukason & Vissak (2017) Process 1 and 3 differed only for a few reasons as the firms following the latter were able to implement or had measures or practices that allowed them to sustain their operational efficiency, particularly with regard to variable short-term assets, even when they were undergoing a reduction in their overall total assets. Moreover, Lukason & Vissak (2017, p. 8) further state that "while for firms following Process 1, financial performance became worse every year, firms following Process 3 could have undertaken an unsuccessful retrenchment… which had, in turn, a notable effect on their profitability and cash flow creation." On the other hand, Process 2 differed the most as it combined elements from Laitinen's (1991) acute, gradual, and chronic declines. Despite revenue efficiency, consistent losses occurred, possibly due to unsuccessful retrenchment or rapid depreciation of outdated equipment, however they maintained positive cash flows until the year preceding bankruptcy (Lukason & Vissak, 2017).

Although Lukason & Vissak (2017) identified 3 failure processes, they found that they presented aspects similar to non-exporters, supporting Lukason et al. (2016) and Lukason & Laitinen (2016) previous findings, also the majority of exporters were classified as “occasional exporters”, a similar definition to “experimental exporters” previously mentioned. Moreover, the authors suggested that old firms are prone to a more gradual decline, but firms with lower international engagement exhibited similar failure processes to non-exporting business, making it challenging to create separate prediction models. However, they noted that when choosing variables in creating BP models, researchers should account that firms experienced high leverage, negative growth, low profitability, and liquidity, however they were able to produce an operating cash flow, also emphasis should be put on focusing on environmental developments of the home market. Furthermore, Lukason & Laitinen (2018) conducted a study aiming to find whether financial predictors for bankruptcy differed between exporting and non-exporting firms. The authors found that while cash flow sufficiency and static solidity are significant predictors for both types of firms, bankrupted exporters differ in profitability, whereas non-exporters show differences in static liquidity. The study suggests that engagement in exporting elevates the importance of profitability and solidity in bankruptcy prediction models. However, Lukason & Laitinen (2018) acknowledge limitations due to a small sample from one country, hindering the study's ability to analyse broader internationalization behaviour.

Overall, the literature has not identified significant differences between exporters and non-exporters, largely because the majority are classified as occasional exporters, which often share many traits with non-exporting firms. However, as it was previously observed, certain distinctions do exist. A study focusing primarily on committed and active exporters could potentially reveal profound differences, thereby facilitating the development of a robust bankruptcy prediction model.

2. Composition of Bankruptcy Prediction Models

2.1 Methodology and Data

In the following subchapter, the author will explain the methodology selected to perform the following study along with the acquired data and analysis. The aim of the empirical part is to utilize 3 distinct tools to create several one-year and three-year bankruptcy prediction models. The former's purpose is to analyse the accuracy and which variables possess a higher degree of significance and how these change when indicators get combined together, while the latter is uniquely to improve the initial models. This section will clarify the dataset utilized for the study, encompassing financial data and from exporting firms. Four key financial metrics and three firms' characteristics will be examined. Logistic regression will be used primarily as the main predictive tool to detects the relationships between these metrics and will then be supported by neural networks and decision trees to try to improve the accuracy of the model.

The data utilized in this study was sourced from ORBIS, a database provided by the Bureau Van Dijk, and was obtained in June 2022. The dataset is comprised of information regarding European exporting firms spanning the years 2016 to 2021 and it is made of both bankrupted and surviving firms within this timeframe. This is because, in bankruptcy prediction modelling, firms are compared in order to analyse if there are common failure aspects in regard to indicators for bankrupt firms and see if they deviate from healthy companies.

Despite the thoroughness of data collection and selection, certain limitations appeared, nonetheless, efforts were made to mitigate these limitations and ensure the robustness of the study's methodology and data analysis. To ensure a comprehensive analysis, 1020 bankrupt firms with varying last reporting years, spanning from 2018 to 2021, were selected due to the limited availability of data for exporting firms. Additionally, 5326 surviving firms were included, with financial data covering the years 2017 to 2019. Given the scarcity of information regarding exporting figures, certain measures were implemented to address this limitation. One of the main constraints of the study has been the scarcity of European exporting data. Consequently, only four countries—France, Croatia, Hungary, and Slovenia—were included, as they presented sufficient and suitable cases for analysis, as outlined in Table 3.

Given that a logistic regression is going to be performed, a balanced dataset is required, with equal number of bankrupted and non-bankrupted firms. This is because imbalanced datasets can result in biased model predictions, where accuracy is skewed towards the majority class at the expense of the minority class. To address this, several adjustments were implemented. Firstly, the number of bankrupt firms and non-bankrupt firms for all countries were equalized to match Slovenia's maximums. Secondly, the number of bankrupt firms was adjusted to match the new quantity of non-bankrupt firms, resulting in a total of 22,376 firms, with an equal split between bankrupted and non-bankrupted cases. This approach ensures a balanced dataset, enhancing the reliability and accuracy of the logistic regression analysis, but also a greater comparison between countries.

Table 3

Bankrupted and non-bankrupted firms per country

Countries	Bankrupt Firms	Non-Bankrupt Firms
France	230	694
Croatia	256	1547
Hungary	72	288
Slovenia	468	2797
Total	1020	5326

Source: Compiled by the author

It's important to note that certain countries might possess different classifications for bankruptcy. For example, as can be seen from Altman et al. (2017) other statuses apart for bankruptcy included “Inactive” or “In liquidation”. In their study for example, the classification for Slovenia, was in fact the latter. This difference can severely impact the creation of bankruptcy models as it may hinder with the correct classification of the firms analysed. Nonetheless, thanks to the ORBIS database, only properly bankrupted firms were filtered and inserted into the dataset.

Regarding the choice of variables, 4 financial indicators and 3 firms characteristics were chosen, which can be seen in table 4. These selected financial ratios have gained considerable recognition within the literature, as evidenced by their inclusion in seminal works such as Altman's (1968) and Altman et al.'s (2017) models. These models are widely regarded as two of the most prominent works in the BP modelling field. Additionally, as demonstrated in Table 1, these indicators have been extensively utilized in the literature and are acknowledged for their efficacy in predictive modelling. Furthermore, in terms of firm selection, small and medium-sized enterprises were mainly targeted. The decision came from the fact that larger companies exhibited fewer instances of bankruptcy, but also due to the lack of extensive data. The size of the companies was calculated by taking the natural logarithm of total assets of the company, which ranged from 3.34 million to 17.49 million Euros in the dataset.

Table 4

Independent Variables

Variables	Description	Domains	Formula
Financial Ratios			
ROA	Return on assets ratio	Profitability	$\frac{Net\ Income}{Total\ Assets}$
ER	Equity ratio	Solvency	$\frac{Shareholders\ Funds}{Total\ Assets}$
NWC	Working capital over total assets Ratio	Liquidity	$\frac{(Current\ Assets - Current\ Liabilities)}{Total\ Assets}$
ATR	asset Turnover ratio	Productivity	$\frac{Operating\ Revenue}{Total\ Assets}$
Firms' Characteristics			
FIRMAGE	Firm age for bank.	Firm characteristic	$Last\ Report\ Year - Incorporation\ Year$
FIRMAGE	Firm age for non-bank.	Firm characteristic	$Year\ 2020 - Incorporation\ Year$
FIRMSIZE	Firm size	Firm characteristic	$\ln(Total\ Assets)$
EXPINT	Export intensity	Firm characteristic	$\frac{Exporting\ Revenue}{Operating\ Revenue}$

Source: Compiled by the author

As mentioned in the literature review, one could argue that bankruptcy models could benefit from tailored variables, but as discussed in the beginning of the chapter, several limitations were encountered. Furthermore, when considering the dataset that will be employed in the analysis, it becomes apparent that more general indicators have to be employed, since firms' information comes from various countries, across different industries, differing sizes and ages and unique degrees of exporting behaviour. So, by using too specific variables, some accuracy might be lost in the development of the model. Despite these issues, as Du Jardin (2009) suggested, the addition of nontraditional financial characteristics could aid in the creation of a well performing model. Therefore, alongside the financial ratios, indicators regarding firms' characteristics have been included to test how well these can predict failure as non-financial metrics and how they improve accuracy in unison with other financial indicators. This approach has been employed quite extensively and as Altman et al. (2017) report models including firms' characteristics can outperform classical models.

As can be seen from table 4, the indicators analysed in this study are firm's age, firm's size, and their exporting intensity. This last one measures the degree of exporting revenue to operating revenue and including it can provide valuable insight into firms' operational structure. As noted by Lukason & Vissak (2017), companies often have varying proportions of export revenue, and these can significantly influence their susceptibility to failure.

Lastly, for this analysis, several predictive tool will be employed. Logistic regression is chosen as the primary method due to its widespread recognition and utilization in bankruptcy prediction literature. Altman et al. (2017), among others, has employed logistic regression in their seminal work. Its popularity stems from its capability to effectively handle larger samples and accommodate categorical predictors, which are prevalent in bankruptcy datasets encompassing firms from diverse countries, industries, sizes, and ages. Additionally, logistical regression offers the advantage of providing interpretable results in terms of odds ratios, facilitating the understanding of how each predictor variable contributes to the likelihood of bankruptcy. Therefore, by leveraging logistic regression, it will allow for a more comprehensive analysis of both financial ratios and firms' characteristics. For these reasons LR will be employed as the sole method for the creations of single-year models since its AI counter tools are less easily interpretable.

However, compared to DT and, especially, NN, logistic regression lacks a bit in the accuracy compared to its AI counterparts, therefore in the creation of three-year bankruptcy prediction models, all tools will be employed to maximise accuracy and check for any differences in prediction power between tools across the general population and the specific countries. Furthermore, the choice of these tools' stems for their widespread use and general consensus within the literature regarding their relative accuracy.

2.2 Results and Discussion

In the subchapter, the author will perform an analysis of the dataset utilizing SPSS. The focus of this part can be dissected into two distinct threads, one revolving around the creation of logistics regressions for the t-1 year for bankrupted firms and 2019 for survived firms and its subsequent analysis. While the other will be focused on the creation of a three-year model to the test the maximum accuracy of the possible models.

Initially, an analysis will be performed to evaluate how much significant are financial ratios by themselves, but, subsequently, these will be pooled together to observe how they collectively act in order to understand which financial ratios have better predictive ability. Furthermore, a distinct analysis will be conducted on the trio of control variables, to test whether firm characteristics stand out as significant indicators within the model. Lastly, an analysis will be made encompassing all indicators, offering a view of their combined influence. Also, the author will analyse the accuracies of each regression model and compare them between bankrupted, non-bankrupted and overall percentages.

Having introduced the steps needed to be taken, the descriptive statistics will now be analysed to gain a clearer understanding of the data. Table 5 presents the descriptive statistics, where N signifies the number of examples in the dataset, accompanied by the median, mean, and standard deviation. Moreover, it's important to note that the financial ratios provided (ROA, ER, and NCW) have been filtered to fall within the range of -1 and 1. However, the Asset Turnover Ratio (ATR) is observed to have values ranging between 0 and 5. Upon closer examination of the descriptive statistics, some differences emerge between bankrupted and non-bankrupted countries. Specifically, the mean and median values of ROA, ER, and NCW are almost all negative for Bankrupted firms. Similarly, ATR exhibits a slight variation, with values leaning slightly more downwards for bankrupted firms compared to their non-bankrupted counterparts.

Table 5

Descriptive Statistics for each Independent Variables

Firms	Statistics	ROA	ER	NWC	ATR
Bankrupted Firms	N	11188	11188	11188	11188
	Median	-0.08	0.05	-0.14	1.08
	Mean	-0.20	-0.11	-0.21	1.55
	Std. Deviation	0.43	0.58	0.56	1.52
Non-Bankrupted Firms	N	11188	11188	11188	11188
	Median	0.06	0.48	0.26	1.54
	Mean	0.09	0.47	0.26	1.78
	Std. Deviation	0.14	0.28	0.31	1.09
Total	N	22376	22376	22376	22376
	Median	0.03	0.29	0.11	1.39
	Mean	-0.56	0.18	0.28	1.67
	Std. Deviation	0.35	0.54	0.51	1.33

Notes: Values have been rounded up to the second digit after comma; The ratios refer to t-1 value for bankrupted firms and 2019 values for survived firms

Source: Compiled by the author

Having introduced the data, the author will now conduct logistic regression analyses to delve deeper into understanding bankruptcy predictors across various groups. Seven logistic regression models will be constructed for five groups each: the general population, as well as France, Croatia, Hungary, and Slovenia individually. In these logistic regressions, a systematic approach will be followed. Firstly, the financial ratios will be tested separately to assess their individual predictive power. Secondly, all ratios will be combined into a single analysis to identify which ratios demonstrate stronger predictive capabilities of bankruptcy. Thirdly, the analysis will extend to include control variables such as FIRMAGE, FIRMSIZE, and EXPINT to evaluate how well firm characteristics can predict failure. Finally, an analysis incorporating all variables will be conducted to assess the overall predictive ability of the model and explore whether combining financial ratios and firm characteristics might enhance predictive accuracy. These steps will be replicated for each group and the results will be tabulated into four separate tables, which will display information per category regarding the Beta coefficients of the variables with their relative signs, and their significance level, marked by asterisks. Furthermore, since significance values can become extremely small, Wald values will also be indicated to showcase, on a more comparable basis, the significance of the variables for each category's models. This will provide a comprehensive overview of bankruptcy predictors and their effectiveness across different contexts.

As the first step, the author will begin by analyzing individual ratios. On table 6 the beta coefficients can be seen for the individual ratios amongst the general population and country-wise. Generally, the ratios follow financial theory, so an increase in these ratios will decrease the chances of bankruptcies. Out of all of them ER seems to have the most significant impact across all datasets, followed by NWC and ROA. The only exception appears to be Hungary where liquidity may play a more significant role than solvency.

Table 6

Beta coefficients and significance of individual ratios

Ratios	Values	Overall pop.	France	Croatia	Hungary	Slovenia
ROA	B	-3.826***	-3.260***	-3.842***	-4.567***	-3.862**
	Wald	2498.217	595.404	587.341	720.400	588.958
ER	B	-3.062***	-2.885***	-2.721***	-3.667***	-3.288***
	Wald	4026.215	959.926	963.311	1082.474	1051.585
NWC	B	-2.353***	-1.942***	-2.180***	-3.364***	-2.291***
	Wald	3708.341	718.147	880.684	1161.727	929.951
ATR	B	-0.132***	0.218***	-0.547***	-0.149***	-0.128***
	Wald	167.869	95.162	438.834	44.238	52.237

Notes. *** sig. value < 0.00001; ** sig. value < 0.001; * sig. value < 0.05; Values have been rounded up to the third digit after comma

Source: Compiled by the author from SPSS

However, when it comes to ATR, individually, it seems to act erratically, this can be seen for example for France, where an increase in asset turnover may signify an increase in bankruptcy risk. Furthermore, apart from Croatia, where it appears to be the main country in which the indicators is highly statistically significant, in Hungary and Slovenia it is not as significant as other variables. Moreover, these findings, generally, are supported from Appendix B which shows the relatively low accuracy for ATR and slightly higher for Croatia. Nevertheless, it's important to note that although ATR comes across as a highly significant ratio, when analyzing statistical results, it doesn't mean that it is therefore a good indicator.

Continuing with the analysis, on table 7 the beta coefficients and significance levels from combined ratios logistics regression are shown. Already from this view certain peculiarities begin to arise amongst the variables. Firstly, ER and ROA, even when combined with other financial predictors, stand out for their significance, and also follow financial theory, which signals their good ability as bankruptcy indicators. The only case in which ROA might not be the best indicator is for Croatia, where it effect, compared to other countries, has relatively dropped compared to table 6. Despite this aspect ROA still performs as a good indicator for bankruptcy, and furthermore it seems to have a great effect in Hungary, where its levels surpass most other countries and has a significance level higher than ER. On the other hand, ER is more spread out and holds a significant effect in all countries, especially in Slovenia where it peaks, while in Hungary is at its lowest.

Table 7

Beta coefficients and significance of combined ratios

Ratios	Values	Overall pop.	France	Croatia	Hungary	Slovenia
ROA	B	-2.229***	-2.428***	-1.336***	-4.132***	-1.868***
	Wald	749.971	259.791	60.082	361.993	127.879
ER	B	-2.829***	-2.661***	-2.990***	-2.295***	-3.741***
	Wald	1601.584	381.986	349.826	199.692	585.558
NWC	B	0.102	0.397*	0.369	-1.317***	0.817***
	Wald	2.585	9.994	6.874	72.946	36.608
ATR	B	-0.281***	0.113**	-0.870***	0.115*	-0.362***
	Wald	367.481	14.285	624.482	10.592	176.026

Notes. *** sig. value < 0.00001; ** sig. value < 0.001; * sig. value < 0.05; Values have been rounded up to the third digit after comma

Source: Compiled by the author from SPSS

However, not all ratios act linearly, for instance NWC tends to act very uniquely and erratically. Compared to the table 6, NWC is not as good of an indicator unlike to the others present in the studies, in fact from the overall population and Croatia's models this variable is not even significant, unlike in the individual regression in which the ratio appeared to be significant. This is because in logistic regression when individual variables are taken individually, they can show to be significant as there are less criterias, however when more are inserted, LR shows which are better identifiers. Furthermore, it can be noted that on the remaining three countries it tends to show more erratic behavior, for example, although Hungary and Slovenia present statistical significance, their Wald levels, respectively 72.946 and 36.608, aren't too high unlike for the values of other ratios, especially in the case of France where its Wald level doesn't even surpass double digits. Moreover, different countries exhibit opposite signs, with France and Slovenia having positive coefficients, this behavior of NWC could be described due to the fact that when companies start failing, they might sell their assets to offset their debts, which can increase their liquidity. However, that might not be necessarily the case since SMEs, because of their smaller size, tend to fail quicker as they might be more susceptible to external shocks, or, as Ooghe & De Prijcker (2008) notes, small companies such as startups may suffer from management or lack of experience, which can speed up the failure process, so there might not be sufficient indicators reported in the t-1 year. Regarding ATR, the ratio presents itself as a better indicator than NWC, however compared to ROA and ER it lacks in predictive power, overall and in the case of Croatia and Slovenia it shows to be an optimal indicator, however in the case of France and Hungary, its significance is much lower.

Turning to the control variables, as showcased on table 8, a logistic regression was performed for all the ratios combined.

Table 8

Beta coefficients and significance of control variables

Ratios	Values	Overall pop.	France	Croatia	Hungary	Slovenia
FIRMAGE	B	-0.036***	0.012**	-0.054***	-0.068***	-0.046***
	Wald	499.912	18.009	190.666	436.571	144.75
FIRMSIZE	B	-0.480***	-1.333***	-0.532***	-0.173***	-0.820***
	Wald	2203.609	1301.986	583.010	46.331	907.28
EXPINT	B	-0.279***	0.907***	0.397***	0.119	-1.044**
	Wald	57.648	53.464	21.227	1.978	13.52

Notes. *** sig. value < 0.00001; ** sig. value < 0.001; * sig. value < 0.05; Values have been rounded up to the third digit after comma

Source: Compiled by the author from SPSS

The most significant indicator turned out to be FIRMSIZE, which possessed high statistical significance for each case, especially for France, only in Hungary the significance isn't as high as other countries, therefore it can be theorized that the size of a firm is not such as a decisive factor in forecasting bankruptcies in the case of their companies. Second to this is FIRMAGE, with high statistical significance in most cases. The only peculiarity regards France, where the significance of the variable is not as marked as in other countries. Similarly to Hungary's relationship with firms' size, in France firm's age doesn't seem to be a significant factor, however if it does, although differing from its counterparts, an increase in firms' age might increase bankruptcy risk. Lastly, EXPINT can be seen as well, however unlike FIRMAGE and FIRMSIZE, its significance as an indicator is far less notable. Overall, the ratio tend to have some significance, especially more for France where it's the highest, however its Wald value equals to only 53.46, which is not very high. The ratio possesses quite erratic behavior, in the case of Slovenia, the indicator is significant only up to 0.001, while for Hungary is not even significant, meaning that there isn't a straightforward connection. Another notable difference is that in the case of France and Croatia an increase in exporting intensity will mean a higher risk of bankruptcy while for Slovenia it's the exact opposite, this could be associated to the fact that a company might be more exposed to international markets, therefore they experience more competition and are more likely to fail. However, it could also be noted already that exporting intensity, although counterintuitive, might not be such an important indicator when considering bankruptcy risk for exporting firms.

Finally, the results of the combined regression analysis are presented in Table 9. Overall, all seven indicators generally demonstrate some statistical significance in the general population model. Notably, emphasis should be placed on FIRMSIZE, ROA, ER and FIRMAGE, which emerged as the most influential financial and control variables, respectively. Consistently, these variables also exhibited high significance across country-specific models, with the exception of FIRMAGE, which did not prove significant in predicting the bankruptcy of French exporters, supporting the findings from table 8. Regarding the impact of individual variables, ROA appears to exert greater influence in Hungary and France, while its effect increased in the case of Croatia. Moreover, ER's impact noticeably dropped in France, Slovenia, and Croatia. Despite some existing issues, ATR seems to act relatively well. However, this is not the case for all scenarios. Similar to what was observed in Table 7, Asset Turnover does not seem to significantly contribute to detecting Hungarian exporting bankruptcies. Moreover, in the case of French firms, the Wald level remains relatively low, signifying a weak effect. Of particular note are the cases of NWC and EXPINT, the former shows varying signs across countries and only demonstrates high statistical significance in Hungary, signifying its unreliability as an indicator. On the other hand, EXPINT does not appear to be as impactful of an indicator overall, presenting a Wald value of 40.215 for the general population and being only marginally significant, with low Wald values, for France and Croatia. As the author theorized before and after reviewing these findings, it can be decisively stated that exporting intensity does not hold much weight as a predictor of bankruptcy for exporting firms. Nonetheless, this might be because the dataset is comprised of several firms differing in their exporting degree. If a group of committed exporters was specifically analyzed, then the research could yield different results as these types of companies rely much more on exporting as their source of revenue.

Table 9

Beta coefficients and significance of all indicators combined

Ratios	Values	Overall pop.	France	Croatia	Hungary	Slovenia
ROA	B	-2.899***	-4.246***	-3.477***	-4.366***	-2.521***
	Wald	844.529	273.919	194.031	382.941	124.833
ER	B	-2.047***	-2.474***	-1.958***	-2.556***	-3.430***
	Wald	652.085	135.548	106.715	194.965	124.833
NWC	B	-0.853***	0.752**	-0.738**	-2.427***	0.636**
	Wald	130.193	15.739	15.869	179.682	12.867
ATR	B	-0.545***	-0.400***	-1.509***	0.054	-0.888***
	Wald	947.352	76.287	756.264	1.911	479.754
FIRM	B	-0.033***	0.006	-0.064***	-0.082***	-0.050***
AGE	Wald	299.963	3.245	133.263	417.765	87.988
FIRM	B	-0.703***	-1.473***	-1.015***	-0.574***	-1.182***
SIZE	Wald	2275.418	1034.249	714.852	226.865	693.918
EXP	B	-0.295***	0.885***	0.622***	0.195	0.098
INT	Wald	40.215	37.802	24.798	2.715	0.059

Notes. *** sig. value < 0.00001; ** sig. value < 0.001; * sig. value < 0.05; Values have been rounded up to the third digit after comma

Source: Compiled by the author from SPSS

Moving onto the accuracy analysis, all of the accuracies of the regression models performed have been listed onto Appendix B. Furthermore, the accuracy of correctly classified bankrupt and non-bankrupt firms is included together with the overall accuracy.

Starting from the individual regression models, ROA turned out to be the best single variable to predict bankruptcy. In the case of the overall population, France and Croatia, the ratios surpassed all other indicators, however, aside its overall accuracy, ROA suffers from a significant setback, which is its difficulty to correctly classify bankrupted firms. The reason for this trend could be that many companies in the year leading up to failure express favourable profitability metrics, which is easily justifiable as the majority of businesses contained in the dataset are SMEs, which tend to fail quicker as they are more prone to external shocks. ER turned out to be the second-best variable but performing as the most accurate individual indicator for Hungary and Slovenia, additionally it exhibits more consistent accuracy between bankrupted and non-bankrupted firms. Regardless, it still shows more favourable predictability for non-bankrupted firms and generally is shows a weak correlation. NWC ranks third in predictability among the financial indicators, following similar patterns to ER but with slightly lower accuracy. ATR, on the other hand, proves to be the least accurate among the financial variables, with relatively poor accuracies, especially in identifying non-bankrupted companies. Only in Croatia does ATR show a slight improvement in predictability, indicating its limited effectiveness as a standalone predictor.

As can be seen in Appendix B, when all of these ratios get combined, it gives an overall accuracy which improves against the main individual variables. The models with accuracies from highest to lowest are as follow: Hungary (82.5%), Slovenia (81.0%), general population (79.1%), Croatia (77.7%) and France (76.7%).

Continuing with the control variables' accuracies, overall, these perform less accurately compared to financial ratios combines, as can be seen from the general population (69.0%). However, in the case of France, its accuracy reaches 80.7% which shows that firm characteristics can be relatively good indicators of possible bankruptcy, as it even outperforms its country-specific financial variables model. In fact, looking at the final models, by combining both financial information and firm characteristics, the accuracy of a model improves drastically, especially in the case of country specific models. The models with accuracies from highest to lowest are as follow: Croatia (89.1%), France (87.9%), Slovenia (87.8%), general population (82.3%), and Hungary (83.8%).

Having covered the first thread of the subchapter, the author will now move onto improving the predictive accuracy of the model by adding 2 additional years of financial information to the firms which have been analysed so far in the thesis. Instead of separately analysing t-2 and t-3 years, all financial values will be pooled into a single model, because as we go further in time before the company's declaration of bankruptcy, the lower the probability of bankruptcy becomes. This aspect can be seen for example in the work of Altman (1968) where the probability of bankruptcy for the firms studied was initially 95.0% in t-1 year, however, it subsequently dropped to 72.0% in t-2 year, and 48.0% in t-3 year.

In order to have a well-rounded approach 3 predictive tools were used, which each created 5 models for the overall population and every country. Alongside logistic regression, DT and NN were chosen as AI tools provide more accurate results than statistical models. In the case of decision trees during the analysis a CRT growing method was employed together with a split sample validation of 50% training sample and 50% test sample. While for neural networks, the following options were chosen to perform the tests: a standardized rescaling of covariates, a partition of 50% training sample and 50% test sample, custom architecture with 2 hidden layers, sigmoid activation function and sigmoid output layer. Moreover, as these AI tools provide different answers for every test taken, 5 different tests were taken for each model made by AI tools, and then the results were averaged to get a more accurate result. Overall, 15 different models were created, and these can be seen in Appendix C. As expected, NN was the most accurate tool (Appendix B) with an accuracy of 92.4%, followed by DT with a percentage of 89.7% and LR with 84.6%, therefore by combining financial metrics from previous years onto one comprehensive model, it helps to achieve a higher predictive accuracy as can be seen from the increase in LR accuracy from 82.3% to 84.6%. Since out of these tools NN provides higher results, its results will be showed, the models with accuracies from highest to lowest are as follow: Hungary (95.0%), Croatia (94,0%), Slovenia (93.7%), France (93.6%), general population (92.4%). (Appendix C)

Conclusion

Throughout this thesis, the primary objective was to develop a series of bankruptcy prediction models tailored specifically for European exporting firms. The aim was to combine essential financial indicators with firm-specific characteristics and exporting data to facilitate an accurate forecast of the probability of potential bankruptcy among companies engaged in international trade. To achieve this objective, firstly a series of single-year logistic regressions were made to measure the significance and effect of ratios in the models, and, secondly, several multi-year predictive models were composed using logistical regression, neural networks, and decision trees to maximize the accuracy.

Across the analysis return on assets and the equity ratio emerge as consistently robust predictors, demonstrating reliability across diverse contexts. On the other hand, net working capital, other than in Hungary, and asset turnover ratio, aside Croatia and Slovenia, tend to act much more erratically. This can also be seen in their predictive accuracy, with return on assets and the equity ratio leading in precision, followed by net working capital and asset turnover ratio. Furthermore, firm size and age prove to be significant indicators of bankruptcy as well, with the exception of France, were firm size lacks relevance. Additionally, when combined with financial metrics, these factors noticeably enhance predictive capabilities. However, exporting intensity turned out to be a relatively insignificant predictor, but it is important to note that this observation may be influenced by the diverse composition of the dataset, which may reflect varying degrees of exporting involvement among firms. Moreover, the integration of three distinct predictive tools into three-year models significantly enhances accuracy. The general logistical regression model, notably, demonstrates an increase in accuracy from 82.3% to 84.6%. Furthermore, neural networks yield markedly improved accuracies across regions: Hungary (95.0%), Croatia (94.0%), Slovenia (93.7%), France (93.6%), and the general population (92.4%). (Appendix C)

Nevertheless, this study introduces several noteworthy contributions to the field. Firstly, the findings highlight the relative insignificance of exporting intensity in predicting bankruptcy among firms, offering a fresh perspective for future research. Moreover, this thesis stands as one of the few works dedicated specifically to bankruptcy prediction for European exporting firms. Additionally, the comparative analysis of financial indicators across countries, together with the comparison of controls against financial ratios, represents a novelty as it offers valuable insights into the complexities of bankruptcy prediction within the context of international trade.

Despite the valuable insights found from the analysis, this thesis is not without limitations. The availability of data for exporting firms constrained the analysis to just a few countries, limiting the generalizability of the findings. Additionally, the scarcity of larger bankruptcy cases among exporters posed challenges in assessing the full spectrum of bankruptcy risks.

In conclusion, this thesis has developed bankruptcy prediction models tailored for European exporting firms capable of classifying firms extremely accurately. Looking ahead, there are several promising avenues for future research in this domain. Additional works could be made regarding export intensity and if it’s a relevant indicator in the case of committed exporters. Furthermore, new financial indicators could be tested alongside more firm characteristics, to see how well these pair.

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Appendix A

Overview of various bankruptcy model types and their Advantages and Limitations

Model	Description	Advantages	Limitations
Multivariate Discriminant Analysis (MDA)	Statistical method that identifies linear combinations of variables to distinguish between bankrupted and healthy firms	- Handles Quantitative Variables	- High degree of Type I errors, misclassification of potentially bankrupt firms as healthy - Possibly confusing results as variable coeff. don't indicate importance - Sensitive to Multicollinearity - Cannot Solve non-linear problems - Sensitive to changes in data - Least Accurate Model in the List (+CBR)
Logistic Regression (LR)	Statistical technique modelling the probability of a categorical outcome based on predictor variables, typically for binary classification	- Less restrictive data needed unlike MDA - Runs well on Large samples - Variable Coeff. represent the importance of variables helping to identify key problem areas - Can handle both Quantitative & Qualitative variables	- Extremely Sensitive to Multicollinearity - Sensitive to changes in data
Artificial Neural Networks (ANN)	Complex AI systems emulating human pattern recognition, they consist of interconnected nodes (neurons) organized in layers to process information, enabling complex pattern recognition, and learning from data.	- Can handle both Quantitative & Qualitative variables - Most accurate Model in the list (+SVM)	- Need a large sample to recognize patterns - Do not provide the weight of a variable on the accuracy of the model - Complex algorithms - Highly dependent on the input variables of authors, bad data may result in bad models - Possible Overfitting or Underfitting - Longer Training times

Support Vector Machines (SVM)	Machine learning algorithm that finds the best hyperplane to separate different classes by maximizing the margin in high-dimensional space	- Can run on smaller samples - Less Sensitive to Multicollinearity - Can handle both Quantitative & Qualitative variables - Most accurate Model in the list (+ANN)	- Do not provide the weight of a variable on the accuracy of the model - Complex algorithms - Possible Overfitting or Underfitting
Rough Sets (RS)	Mathematical approach for sorting and classifying data by identifying similarities and differences in their attributes	- Can run on smaller samples - Can handle both Quantitative & Qualitative variables - Results are easy to interpret and comprehend - Short training times	- Sensitive to changes in data after various samples variations
Cased Based Reasoning (CBR)	Problem-solving method that relies on past experiences or cases to solve new problems by comparing similarities between the current situation and stored cases	- Can run on smaller samples - Can handle both Quantitative & Qualitative variables - Create well updatable BPMs - Results are easy to interpret and comprehend	- Cannot handle large data sets - Sensitive to Multicollinearity Cannot solve - Cannot Solve non-linear problems - Poor Generalizability due to poor accuracy - Least Accurate Model in the List (+MDA)
Decision Tree (DT)	Visual representation of decision-making that uses a tree-like model to classify outcomes based on various features or attributes	- Can handle both Quantitative & Qualitative variables - Results are easy to interpret and comprehend	- Sensitive to changes in data
Genetic Algorithm (GA)	Problem-solving techniques using iterative processes of selection, mutation, and recombination among potential solutions to find optimized outcomes in complex problems	- Suited for variable selection - Create well updatable BPMs - Results are easy to interpret and comprehend	- Longer Training times

Source: Compiled by the author from Alaka et al. (2018)

Appendix B

Accuracies of all one-year logistical regression models

Regressions	General Population			France			Croatia			Hungary			Slovenia		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
ROA	57.6 %	93.3 %	75.5 %	57.1 %	89.2 %	73.1 %	64.7 %	90.9 %	77.8 %	59.3 %	93.9 %	76.6 %	57.1 %	96.8 %	77.0 %
ER	69.6 %	79.4 %	74.6 %	64.3 %	81.5 %	72.9 %	68.1 %	76.3 %	72.2 %	74.2 %	80.7 %	77.4 %	71.7 %	83.2 %	77.5 %
NWC	64.0 %	76.1 %	70.0 %	55.6 %	74.1 %	64.8 %	63.2 %	73.3 %	68.2 %	69.7 %	77.9 %	73.8 %	63.2 %	78.7 %	71.0 %
ATR	63.1 %	44.5 %	53.8 %	47.2 %	64.2 %	55.7 %	71.3 %	57.7 %	64.5 %	65.4 %	43.3 %	54.3 %	65.1 %	44.3 %	54.7 %
Financial Ratios	73.4 %	84.8 %	79.1 %	67.9 %	85.5 %	76.7 %	74.4 %	81.1 %	77.7 %	79.5 %	85.6 %	82.5 %	75.4 %	86.6 %	81.0 %
Controls	66.0 %	72.0 %	69.0 %	80.4 %	80.9 %	80.7 %	70.0 %	75.5 %	72.8 %	67.3 %	75.2 %	71.3 %	74.0 %	78.2 %	76.1 %
All Variables	78.0 %	86.6 %	82.3 %	85.1 %	90.7 %	87.9 %	88.2 %	90.1 %	89.1 %	80.8 %	86.8 %	83.8 %	84.8 %	90.8 %	87.8 %

Notes. 1 refers to the model's accuracy in classifying bankrupted companies; 2 refers to the model's accuracy in classifying non-bankrupted companies; 3 refers to the overall accuracy of the model

Source: Compiled by author from SPSS

Appendix C

Accuracies of all three-year predictive models

Methods	General Population			France			Croatia			Hungary			Slovenia		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
LR	81.8 %	87.4 %	84.6 %	86.2 %	91.7 %	89.0 %	88.7 %	91.7 %	90.2 %	86.7 %	90.1 %	88.4 %	86.7 %	91.9 %	89.3 %
NN	91.5 %	93.3 %	92.4 %	92.4 %	94.9 %	93.6 %	93.5 %	94.5 %	94.0 %	95.6 %	94.3 %	95.0 %	91.9 %	95.5 %	93.7 %
DT	88.6 %	90.8 %	89.7 %	89.3 %	88.8 %	89.0 %	93.1 %	89.8 %	91.4 %	95.7 %	88.5 %	92.1 %	89.6 %	91.4 %	90.5 %

Notes. 1 refers to the model's accuracy in classifying bankrupted companies; 2 refers to the model's accuracy in classifying non-bankrupted companies; 3 refers to the overall accuracy of the model; LR – logistic regression, NN – neural networks, DT – decision trees; percentages rounded up to 1 digit after the comma

Source: Compiled by author from SPSS

Resümee

EUROOPA EKSPORTIVATE ETTEVÕTETE PANKROTI ENNUSTAMINE

Marco Ricci

Pankrotiennustus seisneb erinevate finantsnäitajate ja riskimõõdikute hindamises, et luua mudel, mis suudab prognoosida ettevõtte võimaliku pankroti tõenäosust. Need mudelid hindavad tõenäosust, et ettevõte satub kindlaksmääratud aja jooksul silmitsi finantsraskustega või pankrotiga ning aitavad investoritel, regulaatoritel ja ettevõtetel teha teadlikke otsuseid riskide maandamiseks ja parandusmeetmete võtmiseks.

Pankrotid on ühiskonnas kindlasti vajalikud, kuna need aitavad kõrvaldada kahjumlikud ja kehva tootlikkusega ettevõtted, luues teed tugevamatele ja edukamatele ettevõtetele turul. Neid ebaõnnestumisi tuleks siiski piirata, kuna neil võib olla kahjulik mõju, nagu võis näha eelkõige Lehman Brothersi puhul 2008. aastal. Seetõttu võimaldab mudelite omamine, mis suudavad hinnata ettevõtte finantsseisundit, ettevõtetel pidevalt paremaid tulemusi saavutada ja vältida katastroofilisi pankrotte.

Veelgi enam, tänapäeval on pankrottide mõju tunda kõikjal maailmas. Maailma globaliseerudes muutuvad riigid omavahel tihedamaks ja samamoodi ka kaubandus. Hea näide on Euroopa kontekst, kus põhimõtteliselt on piirid kaotatud, vabakaubandus sisse viidud ja riigid saavad kergemini eksportida. Sellele vaatamata puudub ettevõtete ebaõnnestumise ja täpsemalt ekspordivaldkonna ebaõnnestumiste prognoosimise tegelik kate, mis võib jätta ettevõtted ja nende sidusrühmad haavatavamaks. Seetõttu on käesolevas lõputöös eesmärgiks luua mitmeid pankrotimudeleid, et pakkuda informatsiooni just Euroopa riikidest pärit rahvusvahelistele eksportivatele ettevõtetele.

Enne ennustava mudeli loomist tuleb aga mõista, miks ja kuidas ettevõtted ebaõnnestuvad, eriti kuna pankrot kujutab endast vaid keerulise arengu lõplikku etappi. Analüüsides erinevaid ebaõnnestumiste mustreid, saame aimu, kuidas konkreetsed kontekstid ja ettevõtte omadused mõjutavad ettevõtete ebaõnnestumist. Näiteks võivad väiksematel ettevõtetel olla äkilisemad ja kirjumad läbikukkumise viisid nende nooruse ja haavatavuse tõttu väliste šokkide suhtes, mistõttu võiks nende mudelisse rakendada turustruktuure analüüsivaid näitajaid. Kui suuremate ettevõtete ebaõnnestumise põhjuseid, mis on tingitud nende suurusest ja väljakujunenud positsioonidest, saab hästi seletada õigete finantssuhtarvude vaatamisega, aitab nende olukordade tundmine muutujate valikul kaasa. Lisaks tuleb enne analüüsiga jätkamist valida õige tööriist, mis sobiks uurija eesmärgi ja analüüsitava andmekogumiga.

Selles lõputöös analüüsiti nelja Euroopa riigi ettevõtete andmestikku, milleks olid Prantsusmaa, Horvaatia, Ungari ja Sloveenia. Kahjuks ei jaga paljud riigid eksporditeavet, mis piiras rahvusvaheliste andmete kättesaadavust. Lisaks valiti 7 finants- ja mitterahalist muutujat: varade tootlus, omakapitali määr, uus käibekapital, varade käibekordaja, ettevõtte vanus, ettevõtte suurus ja ekspordi intensiivsus.

Loodi mitu ühe- ja kolmeaastast pankrotiennustusmudelit, igaüks elanikkonna ja konkreetsete riikide jaoks. Üheaastaste mudelite eesmärk on analüüsida seoseid valitud muutujate ja nende vastava konteksti vahel, samas kui kolmeaastased mudelid loodi lihtsalt selleks, et saavutada maksimaalne saavutatav täpsus. Nendel põhjustel valiti ühe aasta mudelite ennustamisvahendiks logistiline regressioon, kuna see annab lihtsaid võrdlevaid tulemusi. Kui mitmeaastaste mudelite puhul kasutati suurima võimaliku täpsuse saavutamiseks logistilist regressiooni koos närvivõrkude ja otsustuspuudega.

Analüüside tulemuste põhjal osutusid seni parimateks näitajateks varade tootlus ja omakapitali suhtarvud, samas kui netokäibekapitali ja varade käibe suhtarv käitus ebastabiilsemalt. Lisaks on ettevõtte vanus ja suurus suurepärased näitajad, kuid ekspordi intensiivsus osutus ebaõnnestumise ennustamisel üsna ebaoluliseks. Lisaks näitasid täpsused, et ettevõtte omadustega seotud finantsteave parandas oluliselt mudeli täpsust ning eriti tänu närvivõrkudele leiti väga täpsed mudelid järgmiste protsentidega: Ungari (95,0%), Horvaatia (94,0%)), Sloveenia (93,7%), Prantsusmaa (93,6%), elanikkond (92,4%).