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Failure prediction of European startup firms

Master's thesis

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

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Abstract

The thesis aims to predict the failure of startup companies in European countries based on their financial reports. In our study, startup equals newly-founded high-tech firms.

Prior researchers have examined the prediction of firm failure through different statistical and machine learning methods with respect to financial ratios derived from accounting information. However, the essence of financial information was not easily applicable in the context of newly-established firms due to their different stages of the operational period. In the previous studies, researchers used to predict a bankruptcy concerning a startup's first and last year's accounting information separately. However, we also incorporated the first and last year's reports together to compare the accuracies of the first and last years' variable groups.

The empirical study focused on 27,533 newly-founded firms in 33 European countries in 2015, including 4,957 failed and 22,576 non-failed firms within the first five-year interval (2016-2020). As previous studies proved the financial ratios to be successful indicators, we focused on using the liquidity, profitability, productivity and solvency in the first and last year's reports and both of them together by applying logistic regression and neural networks techniques. We also observed that contributions of individual financial ratios differed significantly from each other.

Based on our findings, the entire model incorporating both first and last year's reports and using only last year's reports provided more accurate as opposed to the first year's reports. However, there was no noticeable difference between using either last year's or both first and last years' reports.

Keywords:
Bankruptcy, financial ratios, failure prediction, logistic regression, neural networks, high-tech, startups, newly-founded firms

JEL classification: C33, M13, C45, C53

1 Introduction

Nowadays, most firms suffer from financial instability at the initial stages, which leads them to stop running the business, yet some companies succeed. It is undeniable that the failure can potentially occur at any stage of the firm's life cycle, and this applies to both small and newly founded firms. In the past, researchers have used financial ratios to predict bankruptcy, however, some studies mentioned the importance of other factors such as structural inertia, organisational ecology, management inexperience and human capital (Cooper et al., 1994; Hannan & Freeman, 1977, 1984). The main idea of similar studies is to get a fundamental understanding of causes that lead firms to go bankrupt and they can help avoid such a failure. However, it wasn't easy to set a prediction model based on those causes that are not publicly available. Therefore, the signs related to the company's economic status are most likely to be distinguished by the financial ratios.

Age is one of the primary variables to be considered when studying the growth or default rate of the firms. Aspelund et al. (2005) demonstrated that firms' business activities stopped on average 2.5 years after foundation. Another exciting reference was that only 50 % of newly established firms would be able to resist sharp changes or survive within four years, while almost 20 % would run out of business as a failed firm (Mata & Portugal, 1994). However, Konings et al. (1996) found that the tendency for firms to run out of business was the highest during the first three years, and the firms stabilized afterwards. Apart from this, most firms are more inclined to fail in the initial five years since they were first founded because they cannot make a reasonable profit and are less likely to have a chance to survive (Balcaen & Ooghe, 2006). Therefore, we mainly focused on using the first five full years, referring to the approach taken in previous studies. According to Altman (1968), it is easy to calculate financial ratios utilising the firm's financial information. In another paper (Beaver, 1966), the main focus was on five years of financial reports, which made sense regarding the survival likelihood of firms in different industries. Even though the survival rate was low, the previous studies have focused relatively little on the prediction modelling of young firms.

The main object of the thesis is to predict the failure of startup companies in European countries by using the financial ratios based on accounting information according to three variable groups, which are used for measuring the first year, last years' reports and both of them together for comparison to help newly founded high-tech start-up firms to understand whether or they are at risk not. The newly-established high technology firms are vital for economic growth, and on a national scale, they achieve a high level of growth and profitability in the high-tech sphere (Chorev & Anderson, 2006).

Our empirical study will use an advanced artificial intelligence technique called neural networks and classical logistic regression to compare three variable groups. In our approach, we used the reports that belonged to the first, and last year and the model concerning the first and last year together. Also, we have applied those methods for three types of sectors: high-tech, medium-high tech and knowledge-intensive services, to check individual accuracies per variable group. In addition, we have used the same approaches to five European countries with a high number of failed firms to see the difference of industries and countries that could potentially change the overall result. In conclusion, we obtained more accuracy from the neural networks than logistic regression for both years' and last year's models, while accuracy scores varied through countries and sectors. Hence, there was no significant difference between the last year's and both years' predictions.

The structure of the paper is as follows. The objective of the paper was stated in the first introductory part. The second section consists of previous studies about failure prediction, and in the third part, we will touch upon the methods, data, and variables. The fourth section broadly deals with the empirical part to be presented by the presence of neural networks and logistic regression. In the last parts, we will sum up the discussion and conclusion.

2 Literature review

Scholars have studied "failure prediction based on financial information" for more than half a century. These covered "bankruptcy", "the failure prediction of business enterprise", "financial distress", and other phenomena. It is quite difficult to understand the failure of businesses since most authors have focused on the prediction modelling itself rather than understanding what theoretical knowledge stands behind it. Definitions of failure differ considerably among researchers in existing empirical investigations (Ohlson, 1980). The difficulty in understanding the failure of the business stems from a lack of failure ambiguity and how it can be interpreted in different meanings. Since the failure does not take place immediately, there are undoubtedly different stages of decline (Argenti, 1976), and the failure here can be understood in a way that when firms have a scarcity of financial resources, they are getting closer to bankruptcy over time (D'Aveni, 1989). Bankruptcy is an essential word that adequately explained the meaning of failure in most research compared to other keywords (Shi & Li, 2019), however, according to Lukason et al. (2016), bankruptcy was treated as a failure to show the last stage of decline. Financial distress explains the unstable state of the company from a financial perspective, including when the company is not able to pay its short-term debts due to insufficient cash flows generated from operations (Levinthal, 1991). As a broad explanation, the reduction in liquidity, profitability, and borrowing capacity can be regarded as the bottom-line reason that increases leverage (Altman, 1968).

On the other hand, other researchers have approached the problem from different aspects, such as the causes of the firm's bankruptcy. The lack of financial resources and improper management skills can be associated with financial distress (Ashoori & Mohammadi, 2011). However, predicting the failure of firms is not accessible if the sole focus is on the usage of the market-based variables, ecological factors and structure of management, which can potentially have an impact on the survival of firms. The essential financial ratios can be calculated by analysing the publicly available financial information of the firm (Laitinen, 1992). The initial research on failure prediction was mainly based on the financial ratio approaches carried out by Beaver (1966) and Altman (1968). Table 1 shows study frequencies of some financial ratios which are more prevalent among researchers to predict bankruptcy. Apparently, in a period of seventy-seven years, net income/total assets and working capital/total assets were the most cited financial ratios for the prediction that we also had used.

Table 1. Financial ratios in bankruptcy prediction studies

Years 1930-2007			
Factors	**Domain**	**Number of studies**	**Rank**
Net income/Total assets	Profitability	54	1
Working capital/Total assets	Liquidity	45	2
Equity/Total assets	Solvency	27	3
Operating revenue/Total assets	Productivity	10	7
Current assets/Total assets	Liquidity	26	4
Net income/Sales	Liquidity	5	8
Current liabilities/Total assets	Capital structure	13	5
Cash flow/Total debt	Solvency	12	6

Note: We referred (Bellovary et al., 2007) to take number of studies due to each financial ratio.

One of the pioneers (Beaver, 1966) in firm failure prediction used the univariate analysis for his modelling. The primary purpose was to measure the predictive capability of the financial ratios rather than analyse which financial ratio was better. He found out that during the five years leading up to failure, distributions of financial ratios for non-failed firms compared to failed firms are very constant. The gap between them increases gradually as failure approaches. Afterwards, Altman (1968) used the multiple discriminant analysis (MDA) to develop the model initiated by Beaver (1966), and he essentially used the five most crucial financial ratios of profitability, liquidity, turnover, debt to total asset and solvency. MDA model got 94 % accuracy in the initial sample, which is more than Beaver's 78 % accuracy score. In addition, Altman (1968) equalised the proportion of failed and non-failed firms as balanced data in the bankruptcy prediction model to get higher accuracies. In the following years, Deakin (1972) developed a discriminant analysis method based on statistical techniques using 14 ratios, the same as Beaver (1966), however, he excluded the 4th and 5th years because of their high error rates, and his model classified failed and non-failed firms with a 90 % accuracy mainly owing to small sample size.

However, there was a very significant breakthrough among researchers in a new decade. Authors widely criticised linear multivariate discriminant analysis in bankruptcy prediction in the early 1980s, which resulted in alternating new models such as the logit and probit models of Ohlson (1980) and Zmijewski (1984) in referred to (see Prusak, 2018). On the other hand, logistic regression is still one of the most cited statistical methods in recent studies (Shi & Li, 2019). Thus, for first time Ohlson (1980) used 105 failed and 2058 non-failed firms in the logit model with nine financial ratio predictors in three types of estimates to avoid the MDA model's misclassification problems as little intuitive interpretation, covariance predictors matrices and matching procedures. In addition to his contribution to prediction modelling, Ohlson (1980) also discovered in statistical tests that the four financial indicators are significant for predicting bankruptcy. These are size, liquidity, performance and economic structure. However, in contrast to the empirical findings of Ohlson (1980) as well Pastena and Ruland (1986), Peel (1989) found out that the variables measuring the size of the firm and how shares belonging to stakeholders and directors did not play a significant role in predicting the liquidation/merger in logistic regression method. Nevertheless, other variables which belonged to both finance and non-finance indicators differed between survived and financially underprivileged firms with respective high accuracy.

On the other hand, Zmijewski (1984) mainly focused on two main bias reasons caused by selecting a choice-based sample that is influenced directly by the value of dependent variables. Secondly, a non-random sample due to accessible limitations in collecting and assessing the data. He applied these two groups in a bivariate probit model to check the effects of biases on prediction and concluded that choice-based discrimination existed in the model, but it did not affect classification probability or statistical results. He also demonstrated that if the sample distribution amount of failed and non-failed firms is not proportionally balanced, in other words, the number of failed firms exceeds a failed one in the unbalanced dataset, then the model cannot get accurate results for correct classification, which causes poor prediction, because the model follows majority rule (non-failed firms) by ignoring the minority (failed firms) class. McKee and Greenstein (2000) also applied three models (neural networks, logistic regression, iterative dichotomizer) in five imbalanced data sets. Their first finding was that neural networks gave more accurate results than other techniques. They also concluded that imbalanced data creates a bias for non-failed firms, and the models provided poor prediction results of failed firms; however, models can build in better outcomes in balanced data, which decreases the difference between failed and non-failed firms' classes and has a more robust capability to forecast failed firms.

In terms of a breakthrough in the 1990s, there was a propensity to switch from the statistical methods to more advanced techniques to deal with massive data sets. These methods are still prevalent in non-parametric approaches (Prusak, 2018). Recently, the usage of artificial intelligence techniques has spurred a particular interest in researchers, and one such technique was a neural network that was widely used in bankruptcy prediction modelling. However, in contrast to statistical techniques, neural networks require much more sample data for their prediction, and neural networks are more unstable which means over-fitting in the training data set reduces the stability of the prediction. Furthermore, researchers frequently criticize neural networks for difficulties in understanding the results, as these are hard to explain and complex interpretations for decision-makers (Sun et al., 2014), Regardless of drawbacks, neural networks still provide better results in prediction modelling compared to other statistical techniques.

Tam (1991) is one of the earliest researchers in bankruptcy prediction that applied a neural network model. He used 19 financial ratios in discriminant analysis, K nearest neighbours (K-NN), iterative dichotomizer (ID3), neural networks, factor-logit models to predict bank failure in the one-year and two year periods, 118 banks to predict bank failure and according to his result, the neural network performed much better and more accurately than other techniques. But unlike logistic regression, in terms of explanatory ability, neither neural networks nor discriminant analysis provides enough information about the importance of individual variables. In addition to the research mentioned above, Fletcher and Goss (1993) also used neural networks and logistic regression to predict bank failure for 36 observations, and compared their accuracies to find out which is the better forecasting model. Following the conclusion of Boritz et al. (1995), Salchenberger et al. (1992), and Tam (1991), they obtained results in which neural networks outperformed logistic regression. Moreover, Lee et al. (1996) combined statistical and intelligence techniques as a hybrid model in bankruptcy prediction. They used the following three models: MDA-assisted neural networks, an ID3-assisted neural networks, and a self-organising feature map (SOFM)-assisted neural networks. They also took classical MDA and ID3 for the threshold to check the performance of their model. The result was that neural networks had better outputs than statistical techniques, but the superior result was provided by the SOFM-neural networks method. However, Atiya (2001)mainly focused on indicators to improve the performance of neural networks for three-year periods. He selected two input groups, firstly financial ratios and secondly both of financial ratios and equity-based indicators. The first group prediction model provided 81.46 % accuracy, while the second group obtained higher accuracy (85.5 %) using neural networks. Thus, Atiya (2001) demonstrated that the most suitable ratios improved performance and had a more real influence on the model's prediction.

Before coming to other artificial intelligence techniques, regarding statistical methods, there is one additional progressive method called the hazard model, which was used by Shumway (2001) in bankruptcy prediction. He used other static methods (Logit, MDA) for 300 firms between 1962 and 1992 and financial variables used by Altman (1968) and Zmijewski (1984) as input in addition to market-driven variables. Age was another primary indicator for the hazard model because there was no alternative for determining how long a company was operating. He showed that the hazard model performed well or better than other static models, and market-driven variables played a key role in the hazard model at the same par with financial ratios.

After 2000, researchers improved neural networks to obtain higher accuracy and started to apply new artificial intelligence techniques to bankruptcy prediction. The most commonly used artificial intelligence techniques for failure modelling scope are neural networks, support vector machines, decision trees, genetic algorithms, fuzzy, rough sets, data mining, case-based reasoning, and genetic algorithms. However, neural networks have superior popularity in bankruptcy prediction among researchers (Ravi Kumar & Ravi, 2007; Shi & Li, 2019; Veganzones & Séverin, 2020). On the other hand, some research also compared these techniques with neural networks to better understand which method provides more accurate results. For example, Shin et al. (2005) support vector machine (SVM) and backpropagation neural networks (BPN) with ten financial ratios to predict bankruptcy and concluded that SVM gave better results in training data as sample size decreased in feed-forwarding compared to BPN while Kim (2011) discovered that although SVM accuracy (95 %) exceeded neural network (91 %), misclassification rates were better and preferable for the neural network. Additionally, Chen and Du (2009) showed that BPN outperformed the data mining clustering technique with better accuracy prediction.

Table 2 demonstrates relevant information from some studies on firm failure prediction topic and as it can be seen, in the new century, neural networks and logistic regression were more popular and most of researchers preferred financial ratios for predicting bankruptcy and regarding recent literature about our topic, Lukason et al. (2016) investigated the failure process among young manufacturing micro firms in 11 countries within a six-year interval. The four financial variables applied were profitability, liquidity, solvency and leverage variables. The primary method was based

Table 2. Analysis of relevant studies

Year	Author(s)	Data	Method(s)	Variables	Max. acc.
1968	Altman	66	MDA	WC/TA, RE/TA, EBIT/ TA, equity/TD, Sales/TA	95 %
1980	Ohlson	105	LR	Size, WC/TA, TL/TA, CL/CA, NI/TA, Funds/TL	96.12 %
1984	Zmijewski	129	Probit	NI/TA, TD/TA, CA/CL	59.9 %
1991	Laitinen	40	MDA	ROI, CF/NS, Quick ratio, CF/TD, NS/TA, TD/TA	89.7 %
1991	Tam	118	MDA, ID3, KNN, NN	TC/TA, ROAS, TE/TA, TI/TA	96 %
2001	Shumway	300	HM, LR	WC/TA, EBIT/TA, NI/TA,TL/TA	75 %
2011	Kim	33	NN, LR, SVM, MDA	Current ratio, Quick ratio, Debt/Equity, FA/LTC, AT	95 %
2015	Tian et al	17,570	DH, LASSO, DD	CL/TL, CA/CL, Funds/TL CL/TA, QA/CL, NI/TA, RE/TA	68.2 %
2020	Yolanda et al	6,167	LR, NN	TA, ROA, CL/CA, WC/TA, R/NE	69.9 %

Abbreviations: MDA - Multiple discriminant analysis, LR - Logistic regression, ID3 - Iterative Dichotomizer, KNN - K nearest neighbours, NN - Neural networks, HM - Hazard model, SVM - Support vector machine, DH - Discrete Hazard, DD - Distance to default, WC - Working capital, RE - Retained earnings, TA - Total assets, EBIT - Earning before interests and taxes, TD - Total debt, TL - Total liabilities, CL - Current liabilities, CA - Current assets, NI - Net income, ROI - Return on investment, CF - Cash flow, NS - Net sales, ROAS - Return on average sales, NS - Net sales, TI - Total income, TE - Total expenses, FA - Fixed assets, LTC - Long term capital, R - Revenue, NE - Number of employees, QA - Quick assets.

on factor and cluster analysis. The homogeneous groups were defined concerning factor scores, and he concluded various failure process changes between either 4 phases or 2 phases for firms by their age.

However, Altman (1968) used MDA and Logistic regressions applied to the data of companies from 31 European and three non-European countries to evaluate the performance of Z-score in an international context. They applied MDA and seven logit models by adding control variables in addition to 4 financial ratios. After using the classification performance method for European countries to estimate the change of coefficients, the accuracy did not improve remarkably. Therefore the output gained from the MDA was regarded as robust across countries over time. Fuertes-Callén et al. (2020) applied extra factors such as non-financial variables (structural inertia, human development) to the prediction model in addition to financial ratios (profitability, productivity, leverage, liquidity) in the eight-year operation period. According to their hypothesis, companies in a healthy situation will be more successful in avoiding bankruptcy than others facing difficulties in the early years of operations. Fuertes-Callén et al. (2020) applied data from 6,167 newly-founded Spanish start-up companies to Logistic regression, neural networks (multilayer perceptron and radial basis function) and CHAID decision tree techniques, while neural networks provided maximum accuracy (69.9 %) in the test sample.

3 Study design

3.1 Data

Our study's data was extracted from the ORBIS database and consisted of 27,533 firms, including 4,,957 failed and 22,576 non-failed firms. In the dataset, we focused on 33 European countries in which information regarding financial reports was available. Our primary focus was to predict bankruptcy for newly-founded high-tech startup companies. The startup is regarded as an area of business with at least one employee for the given time, which neither integrates with any other company nor works under the branch of any existing firm. However, some authors stressed that startup firms mainly run innovative processes (Spender et al., 2017). Additionally, the newly-established start-up firms are small and pay more attention to research and development (RD). This method helps define and analyse the expenses and bring out the percentages of RD expenses of operations costs of business enterprises. There are mainly two ways of identifying the high-tech industry:

- Sectoral
- Production

The sectoral is a pool of business areas in line with the technology intensity following the European Classification of Economic Activities (NACE) classification code with the first two digit level. The product method is related to research and development intensity calculations by product groupings using the Standard International Trade Classification (SITC). We obtain our focus on the sectoral selection using three types of industry:

- High-technology (HTEC)
- Medium high-technology (MHTEC)
- Knowledge-intensive services (KIS)

Table 3 below provides an overview of the number of companies, business areas and NACE codes for every high-tech manufacturing industry we used in our study. The central part of the

Table 3. Sector analyzed

Manufacturing industries	NACE Rev, 2 codes	Business areas of enterprises	Number of companies	Total
High technology	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations;	132	871
	26	Manufacture of computer, electronic and optical products.	739	
Medium high technology	20	Manufacture of chemicals and chemical products.	950	4375
	27 to 30	Manufacture of electrical equipment; Manufacture of machinery and equipment n.e.c; Manufacture of motor vehicles, trailers, and semi-trailers; Manufacture of other transport equipment.	3425	
Knowledge-intensive services	58 to 63	Publish activities; Programming and broadcasting activities; Computer programming, consultancy, and related activities; Telecommunications; Information service activities; Motion picture and television program production, sound recording.	20544	20546
	64 to 66	Financial and insurance activities.	1	
	69 to 75	Legal and accounting activities; Activities of head offices, management consultancy activities; Architectural and engineering activities, technical testing, and analysis; Scientific research and development; Advertising and market research; Other professional, scientific, and technical activities; Veterinary activities.	1	

[1]ource: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec$_{e}sms_{a}n3.pdf$

data consists of knowledge-intensive services (20546), while the medium-high technology and high technology categories include a total of 4375 and 871 newly-founded startup firms respectively.

There were some missing values in financial reports which means the firms did not submit their reports either at all or correctly by the deadline for consecutive years in the data. For instance, in Estonia, it is legally allowed for a firm to submit their annual financial information with a delay of 6 months, without any penalty. Here we can explain that the latest data for the running company can vary in range up to 1.5 years. Some firms did not provide their financial reports on purpose right after they felt the risk of going into insolvency (Lukason, 2013). In line with the rules of the Estonian Commercial Code, as the company is warned for late submission, it has added six months to send that missing yearly statement. Suppose the company does not follow the rules after the first warning. In that case, the government will stop the company's operation, and their registration of commercial activity will be deleted compulsorily. It was hard to understand a given company's overall status by focusing on the financial report in the first year. That scarcely explained the activity of companies from the perspective of economics, especially for those companies which started running near the end of the year. Therefore, we merged first-year reports with 2016 because the foundation year 2015 reports are always partial. In our empirical study, we used the information submitted by the newly-founded firms within five years for 2016 and 2020.

Aside from annual financial information, the data also include whether the company went into default or not, followed by status change. If the firm is legally announcing its bankruptcy proceeding voluntarily or following the mandatory liquidations, we deem it a failed firm.

Our data includes the following three types of liquidation:

- Mandatory liquidation because of insolvency.
- Mandatory liquidation because of legal non-compliance.
- Voluntary liquidation because of different reasons.

ORBIS database enables one to distinguish from others for some countries in accordance to government financial regulations while they are all in one pool in some countries. Therefore, it should not be fair to associate the regulations of one country with others, which means that voluntary liquidation should not take precedence over actual insolvency cases. The output variable consists of dummy variables in the data set that indicate 0 if the company is active, while one shows that the company is not solvent.

The companies that went into default fast did not tend to present any financial information. Still, again we relied on the status quo of information available without checking when the last report was submitted. When the firm can no longer settle its debts, managers might bring an insolvency motion to the judge. This situation is the most common for Spain companies (Camacho-Miñano et al., 2013).It is the same for all countries, while legislation and implementation vary. After a bankruptcy, most businesses are liquidated, although some are reconstructed successfully. Unfortunately, only a tiny percentage of companies can recover from bankruptcy. Most studies (for example Altman, 1968; Beaver, 1966) regarding bankruptcy focused on the analysis of five years. Therefore, we analysed the first five years since the initial running of the company to predict bankruptcy by using financial ratios.

3.2 Variables

The financial variables used in our modelling are the financial ratios as set out in Table 4. They have been selected following the essence of the theory and how the previous studies set the model based on those variables.

Table 4. The Variable selection

Variable	Characteristics	Formula
Liquidity	Working capital over Total assets	$\frac{(\textit{Current Assets (CA)} - \textit{Current Liabilities (CL)})}{\textit{Total Assets (TA)}}$
Profitability	Return on Total assets	$\frac{\textit{Net Income (NI)}}{\textit{Total Assets (TA)}}$
Productivity	Asset Turnover ratio	$\frac{\textit{Operating Revenue (OR)}}{\textit{Total Assets (TA)}}$
Solvency	Shareholder Equity ratio	$\frac{\textit{Equity}}{\textit{Total Assets (TA)}}$

Starting with profitability is one of the critical variables to show the consistency of a company. Profitability is a financial metric that compares a company's profit to its revenue. More efficient organisations make more profit as a percentage of their revenue than inefficient organizations, which have to spend more resources to generate the same profit. Short-term profitability can be attained by selling assets that generate quick profits. This kind of profitability, however, is not sustainable. A company should have a business model that permits it to earn from its operating activities, or it will eventually go bankrupt. In addition, profitability is one of the primary factors that can be used to determine the valuation of a company.

The second variable used in our model is the asset turnover ratio or productivity. The asset turnover ratio compares the valuation of a firm's assets to the valuation of its number of items sold or revenue. It is one of the primary indicators that measures how effectively a firm uses its assets to produce income. A low asset turnover ratio suggests that a firm is not effectively leveraging its assets to grow revenue.

On the other hand, the third independent variable, i.e. net working capital to total assets, belongs to liquidity, which measures the company's ability to pay off its debts within a short time. With respect to ratio, working capital is the gap between current assets and current liabilities, calculated by dividing total assets to define a company's short-term solvency. By comparing a company's total current assets to the company's total assets, the working capital to total assets ratio assesses a company's capacity to meet the short-term financial obligation, because this ratio might provide some insights into the company's liquidity; in other words, the percentage of remaining liquid assets relative to the company's total assets.

The last financial ratio is the shareholder equity ratio associated with solvency. The shareholder equity ratio demonstrates the percentage of the firm's assets produced through the issuance of stock shares plus accumulated profits rather than debt. When the ratio decreases, the firm has utilised more debt to finance its assets. It moreover displays what proportion of assets business partners might obtain if the firm is in voluntary obligation to stop running the operation. The shareholder equity ratio is calculated by denominating total shareholders' equity by the firm's total assets and is acknowledged as a ratio.

These are the essential variables that have been used in our prediction modelling, the importance of which have been scientifically proved by other researchers studying the area of firm failure prediction.

3.3 Methods

As the goal of the paper is to create a failure prediction modelling for the newly-established startup firms, mainly statistical and artificial techniques, have been applied to predict bankruptcy since the 1960s. We selected one technique for each of them: logistic regression for statistical approach and neural networks for artificial intelligence. The logistic regression is used to predict a binary class that shows whether the company has failed or not based on historical information. Regarding the working principle, logistic regression applies the logistic function to constrain the outcome of a linear equation between 0 and 1 rather than adopting a straight line or hyperplane.

Function for logistic regression is calculated as below:

$$f_\theta(x) = \frac{1}{1+e^{-\theta^T x}} \tag{1}$$

From the aspects of feature importance, the advantage of logistic regression is the capability of interpretation for individual independent variables; in other words, it can demonstrate how much every input contributes to the model in terms of bankruptcy prediction. However, other techniques cannot provide valid information about a single independent input contribution in prediction, this applies to even the most advanced techniques such as neural networks. Our second method used to get a prediction is neural networks which belong to artificial intelligence techniques. The neural networks allow for more in-depth analysis and improved decision-making by creating more efficient and accurate prediction models. Compared to traditional statistical methods, one of the main advantages of neural networks is adaptability and eliminating random effects. Additionally, neural networks, for instance, can predict both categorical and continuous outcomes. However, because neural networks can build incredibly complicated models with several layers, they might be challenging to interpret in terms of business insights. Concerning predictors, the values of the input variables are fed into the algorithm as an input layer using a neural network, and the input layer helps build a hidden layer with unseen nodes. Adding more hidden layers per network means adding more parameters to the model. We used two hidden layers by applying the sigmoid function in each layer to fit more complex tasks in bankruptcy prediction.

Since the logistic regression is easily affected by outliers, normalisation has been applied to transform data. Therefore, we used one of the outlier detection methods called winsorisation, that substitutes the tiniest and highest values with the closest observations, which defined upper and lower limits by authors. After that, as we mentioned in the data subsection, we have 4,957 failed and 22,576 non-failed firms; hence, non-failed firms will have dominance over the failed ones. As we aimed to understand how non-failed firms are distinguishable, this can be achieved by equalising groups. Otherwise,non-failed firms will be classified with the maximum possible accuracy. Therefore we used the method called synthetic minority oversampling technique (SMOTE) to decrease bias and create balanced data. This helps to prevent rule of majority vote, which mostly happens when the data is insufficient for one class. Next, we divided the dataset into train and test samples with a 50/50 proportion and ran our models with logistic regression and neural networks. We used four individual variables (liquidity, profitability, solvency, productivity) in the first, last, and both groups. This approach was used to compare the accuracy between when the company started operating and at which stage it went to bankruptcy.

4 Result

Before the transformation and descriptive statistics, we applied the SMOTE method. It helped to balance the data to prevent the majority vote rule so that it can easily be seen from the figures that the numbers for failed and non-failed are equal. Regarding the transformation, once we defined the outliers, instead of the outliers elimination method, we rectified it with the winsorisation method. We winsorised the data by setting a lower limit to 0 and an upper limit to 10 for the productivity ratio. However, we used -1 and 1 for the other financial variables respectively. Table 5 provides descriptive statistics with mean, minimum, maximum and standard deviation of financial ratios based on first and last year's reports for failed and non-failed firms. Looking at the details, except the last year's productivity, the mean values for non-failed firms are relatively higher than that for failed firms.

In fact, one cause for this could be that assets in the denominator start decreasing very quickly because of accumulated losses, as a result the quotient mathematically becomes abnormally large. Another explanation might be that as firms reach closer to the financial stage of bankruptcy, they tend to increase their level of production to survive, while non-failed firms prefer to keep stable. Therefore, the mean value of failed firms exceeds that of non-bankrupted firms in the last year's report. It can be seen from table 5 that there is an optimistic tendency for liquidity mean of non-failed firms from first to last year's report (0.25 to 0.29), whilst the pattern is not the same for failed firms decreasing from 0.18 to 0.14 in five years interval.

On the other hand, we used the individual ratios for both first and last year's reports in logistic regression to get accuracy, as shown in table 6, by measuring the impact of each financial ratio on the status. Logistic regression provides enough information about the importance of individual variables in terms of explanatory ability compared to other techniques (Tam, 1991). Afterwards, we ranked the accuracy of financial ratios for the first and last year's reports. Here we can observe that the profitability is by far the highest (58.6 %), whereas the productivity experienced the lowest figure (51.5 %) for the first year. There is a slight difference between liquidity (52.9 %) and solvency (53.5 %). When it comes to the last year, there is almost the same pattern except productivity was slightly lower (50.6 %) compared to first-year productivity (51.5 %). The profitability of last year's report, which made up almost (62 %) differed with a three percentage point increase instead of

Table 5. Descriptive statistics of data

First year					
Status		**Liquidity**	**Profitability**	**Productivity**	**Solvency**
Non-failed	Number	22576	22576	22576	22576
	Mean	0.25	0.08	2.1	0.33
	Maximum	1	1	10	1
	Minimum	-1	-1	0	-1
	Standard deviation	0.53	0.47	2.31	0.51
Failed	Number	22576	22576	22576	22576
	Mean	0.18	-0.1	2.01	0.24
	Maximum	1	1	10	1
	Minimum	-1	-1	0	-1
	Standard deviation	0.59	0.52	2.64	0.59
Last year					
Non-failed	Number	22576	22576	22576	22576
	Mean	0.29	0.5	1.61	0.37
	Maximum	1	1	10	1
	Minimum	-1	-1	0	-1
	Standard deviation	0.53	0.39	1.99	0.53
Failed	Number	22576	22576	22576	22576
	Mean	0.14	-0.17	1.85	0.18
	Maximum	1	1	10	1
	Minimum	-1	-1	0	-1
	Standard deviation	0.67	0.54	2.77	0.68

the first year's one. This is the highest accuracy among all variables in total ranks. By total ranks, while productivity contributed the minor usefulness, profitability was the best indicator among other variables, and Dimitras et al. (1996) also highlighted importance of profitability after reviewing 47 articles. Following that, according to Fuertes-Callén et al. (2020) profitability accounted for much more than liquidity, 73.3 % and 65.1 %, respectively.

Table 6. Ranking of variables

Variable groups	Financial Ratios	Accuracies	Ranks	Total ranking
First Year				
	Liquidity	52.9 %	3	6
	Profitability	58.6 %	1	2
	Productivity	51.5 %	4	7
	Solvency	53.5 %	2	5
Last Year				
	Liquidity	55.6 %	3	4
	Profitability	61.8 %	1	1
	Productivity	50.6 %	4	8
	Solvency	56.6 %	2	3

Aside from statistical techniques such as logistic regression, there have been huge improvements in bankruptcy prediction modelling in the last 30 years by applying artificial intelligence and data mining techniques. Trusting in the results and the theory standing behind it, the neural networks used in our prediction modelling ended up with a reasonable output depending on three variable groups.

In table 7, the first year in both logistic regression and neural networks almost provided a similar accuracy of 59.2 % and 58.8 % ,respectively. However, last year's results accounted for 64.1 % for neural networks and more than two percentage points of decrease for logistic regression (61.8

%). If we look at the overall accuracies of both years' variable groups, neural networks (65.0 %) produced a considerably more accurate result, up to 4 per cent compared to logistic regression (61.9 %). Meanwhile, this accuracy is also the maximum for all logistic and neural networks we have already obtained. As a leading example to compare used techniques, there was a noticeable difference between neural networks and logistics regression, whose accuracies were 82.4 % and 71.3 %, according to findings of Fletcher and Goss (1993).

Regarding failed and non-failed status, it can be seen easily in table 7 that non-failed predictions provided considerably higher accuracy than failed ones, and a lower classification rate negatively affected the overall scores of our models. At the same time, the neural networks model had performed better than logistic regression for failed prediction per variable group. However, logistic regression executed better accuracies for first (68.8 %), last (75.3 %) and both (72.8 %) years variable groups for failed firms. In any case, we took into consideration the overall scores provided by the models and we can conclude that the performance of neural networks was better than that of logistic regression. In terms of variable groups, both (65.0 %) and last (64.1 %) years performed reasonably well in comparison with the first years (58.8 %) while there was no a significant difference between last year and both years' variable groups.

Table 7. Model accurarcies of whole population

	Logistic			Neural Networks		
	Failed	Non-failed	Overall	Failed	Non-failed	Overall
First Year	49.5 %	68.8 %	59.2 %	58.1 %	61.5 %	58.8 %
Last Year	48.3 %	75.3 %	61.8 %	56.7 %	71.6 %	64.1 %
Both Year	50.9 %	72.8 %	61.9 %	60.0 %	70.0 %	65.0 %

Beforehand, we had used the modelling for the whole population. We applied the same logic to three individual sectors to precisely identify their prediction accuracies for comparison. We categorised the sectors into three groups that accordingly belong to Sector 1 (high technology), Sector 2 (medium-high technology) and Sector 3 (knowledge-intensive services). Table 8 below shows the overall accuracy of first, last and both years variable groups based on sectors. We were considering the results for neural networks and logistic regression, the former lead to an accurate performance over the latter. However, there is an exception that the accuracy for the first-year variable group of sector 3 provided almost a similar result for logistic regression and neural network (59.2 % and 59.1 % respectively).

Additionally, the first year variable group's accuracies did not make a massive difference in the accuracy score in logistic regression belonging to three sectors. This might be related to the assumptions that some firms perhaps started working from the second half or closer to the end of the year; therefore, unlike the first year, some financial reports would definitely have been submitted for the last year, which also provided for better classification accuracy. Regarding comparison, both years and last year's reports produced moderately similar results in the used models per sector. However, the neural network of both years' reports for sector 1 provided the best output (71.9 %) when compared to sector 2 (69.8 %) and sector 3 (65.0 %). The apparent reason behind this is that the ratios calculated from accounting information can make them end up with different outputs due to the various business models of each sector. For instance, service firms do not acquire a significant investment for non-current assets, which does not cause any change in financial statements. Therefore, knowledge-based service firms are anticipated to have the lowest accuracy in that case. Also, according to the above-mentioned reasons, sector 1 took over sector 2 and sector 3 for every variable group in logistic and neural networks models. Compared to the previous studies,Fuertes-Callén et al. (2020) used high-technology firms in the same manufacturing industry as sector 1. However, their model provided a maximum of 69.9 %, whilst in our case, the neural network brought about 71.9 % for high-technology firms.

With respect to the techniques' comparison of the model, it should be highlighted that although logistic regression classified more precisely for non-failed firms compared to neural networks for each sector, however, the overall scores decreased due to a higher misclassification rate of failed firms because neural networks have balanced accuracies in failed. Non-failed predictions compared

Table 8. Model accuracies of sectors analysed

		Logistic			Neural Networks		
		Failed	Non-failed	Overall	Failed	Non-failed	Overall
	Years						
Sector 1	First	52.1 %	70.1 %	61.1 %	58.8 %	68.8 %	63.9 %
	Last	43.3 %	77.8 %	60.5 %	66.6 %	72.8 %	69.8 %
	Both	60.3 %	74.7 %	67.5 %	70.9 %	72.9 %	71.9 %
Sector 2	First	45.4 %	73.5 %	59.5 %	56.0 %	65.2 %	60.6 %
	Last	47.0 %	78.5 %	62.7 %	67.0 %	69.3 %	68.2 %
	Both	48.4 %	76.3 %	62.4 %	65.4 %	74.2 %	69.8 %
Sector 3	First	50.7 %	67.7 %	59.2 %	53.4 %	64.8 %	59.1 %
	Last	48.1 %	74.8 %	61.4 %	62.7 %	68.1 %	65.4 %
	Both	51.5 %	72.1 %	61.8 %	60.9 %	70.2 %	65.5 %

to logistic regression which provided lower accuracies in failed firms. In other words, logistic regression performed better in the classification of non-failed firms ,while neural networks had more accurate results for an overall score.

After analysing the results for whole populations and sectors, we queried whether some countries might have a pretty significant impact on the development, and in our understanding, those are the countries that have a great number of failed firms. You can see the number of failed firms for each country demonstrated in table 9. Therefore, we selected those leading countries (Italy, France, Russia, Norway and Great Britain) that would have a more negative impact on the performance of our models as compared to the rest of the countries for prediction.

As expected, last year's and both years' variable groups had significantly better performances than the first year's accuracy for all selected countries provided in table 10. However, there does

Table 9. Number of failed startup companies per country

Country ISO code	Num. of failed firms	Country ISO code	Num. of failed firms	Country ISO code	Num. of failed firms
AT	6	**GB**	**292**	NL	2
BA	3	HR	147	**NO**	**359**
BE	8	HU	95	PL	50
BG	91	IE	3	PT	202
CZ	17	IS	15	RO	75
DE	8	**IT**	**1562**	RS	30
DK	83	LT	1	**RU**	**727**
EE	15	LU	3	SE	139
ES	125	LV	104	SI	48
FR	**575**	MK	4	SK	24
FI	100	MT	6	UA	38

not seem to be a vast difference between the accuracies of the model based on last year's and both years' financial reports. For instance, Italy's accuracy for the first year made up almost 63 % in the neural network. However, the same was not expected with last and both years that reached 70.9 % and 71.2 %, respectively, while Ciampi (2015) obtained 74.7 % accuracy by using small Italian firms to predict bankruptcy in logistic regression was similar to our results. Concerning techniques comparison, accuracies for France were the lowest for all three variable groups in neural networks. At the same time, prediction for Russia provided minimum accuracies among countries in logistic regression, followed by France. In addition, it is observable that neural networks performed the best prediction for Italian companies for every variable group. However, there was an inconsistent trend for logistic regression even though the highest classification rates belonged to Great Britain in the first (63.4 %) and both years' (69.1 %) variable groups. Nevertheless, the prediction of Italian companies was the most accurate result (68.0 %) for last year's variable group pursued by Norway with 67.56 % accuracy. Potential reasons why Italy had reached the higher prediction capability might be associated firstly with the fact that Italian firms have by far the highest accuracy for the non-failed firms group and second by Italy has a more significant number of failed firms (1,562) applied in the model.

Table 10. Model accuracies of leading countries

		Logistic			Neural Networks		
		Failed	Non-failed	Overall	Failed	Non-failed	Overall
	Countries						
First Year	Italy	47.5 %	76.2 %	61.8 %	51.8 %	73.9 %	62.8 %
	France	48.8 %	67.3 %	58.0 %	14.4 %	92.3 %	54.1 %
	Great Britain	61.0 %	65.9 %	63.4 %	76.4 %	52.1 %	64.0 %
	Russia	44.1 %	69.9 %	57.0 %	46.8 %	68.1 %	57.5 %
	Norway	56.5 %	62.8 %	59.6 %	54.0 %	63.0 %	58.5 %
Last Year	Italy	54.2 %	81.9 %	68.0 %	60.9 %	81.1 %	70.9 %
	France	52.8 %	71.2 %	62.0 %	38.1 %	84.4 %	61.0 %
	Great Britian	56.1 %	74.4 %	65.2 %	56.3	83.8 %	69.7 %
	Russia	52.8 %	64.8 %	58.8 %	57.9 %	65.3 %	61.6 %
	Norway	64.2 %	70.9 %	67.56 %	62.6 %	72.5 %	67.5 %
Both	Italy	56.0 %	80.3 %	68.2 %	64.5 %	77.8 %	71.2 %
	France	53.1 %	71.4 %	62.3 %	39.4 %	83.6 %	61.9 %
	Great Britain	63.1 %	75.6 %	69.1 %	73.5 %	68.9 %	70.9 %
	Russia	51.5 %	66.7 %	59.1 %	66.2 %	68.9 %	67.5 %
	Norway	56.5 %	62.8 %	64.5 %	59.1 %	73.7 %	66.1 %

Based on our findings, we came to the conclusion that last and both years had considerably better performances than the accuracy scores of first year variable groups, but last year's prediction accuracies are slightly different from both years' variable group. We can conclude that taking into consideration last year's financial reports can be more efficient than the first year's reports to predict bankruptcy for newly-founded startup firms.

5 Discussion

We proposed that examining the first five years of financial information of high-tech startup companies and developing the model based on three variable groups extracted from the financial accounting information was of crucial importance in the prediction modelling of bankruptcy. Regarding the independent variables, some authors Gimmon and Levie (2010) and Hannan and Freeman (1977) have mentioned the importance of other factors such as human capital, market-based values, and macroeconomic trends that would be able to play a role in predicting the failure of firms, however, they were not very useful in predicting company failure through financial variables. From the previous studies, we figured out that the main objective of using the financial ratios was to evaluate business models against other non-financial variables (Altman, 1968; Beaver, 1966). In addition to that, the financial reports are publicly available from which it is feasible to calculate those required ratios to be used in the modelling (Laitinen, 1992). he most crucial variables that were very often applied were liquidity, solvency, profitability and productivity (Dimitras et al., 1996; Sun et al., 2014).

The objective focus of the discussion encompasses the importance of profitability for the failure of high-tech newly founded startups. This is an essential finding in understanding the contribution of every financial ratio to the prediction models individually, as shown in table 6. Because young firms are not capable of saving up cumulative profits, they will most likely have low financial ratios. As a result, it will lead to a faint chance to continue operations compared to mature firms (Altman et al., 2017). We demonstrated that profitability using the measure of an organization's profit relative to its expenses took priority in terms of better predictability, followed by capital structure solvency compared to other financial ratios. Contrary to Fuertes-Callén et al. (2020) we did not find a substantial contribution of liquidity, which measures a company's ability to pay short-term obligations of one year or less to the prediction model. We speculate that this might be due to volatile characteristics of liquidity in comparison to profitability in the early years of operation for newly-founded startup firms because young firms might be more likely to have issues with liquidity, even up to constantly tackling liquidity problems, since they have not had possibilities to build up liquidity reserves. This is also, to some extent, contrary in comparison to the findings in Beaver (1966). We agree with Fuertes-Callén et al. (2020) from the standpoint of liquidity's powerful effect on bankruptcy prediction. However, the results of our research found clear support for the superior influence of profitability to other financial ratios, including the liquidity we used. Profit is the primary metric used to evaluate a company's stability and the primary interest of shareholders. Moreover, a profitable firm may not have enough liquidity since most of its money is invested in projects. A company with more liquidity may not be lucrative, because excess funds have not been appropriately used in the case of high-tech companies. It is also worth discussing these exciting facts revealed by the results of Altman et al. (2017), namely that negative profitability is the most influential signal which leads to potential bankruptcy in the future ,even though last year's reports may not examine the financial circumstance of the company (Lukason & Laitinen, 2019). Aside from this, our article sheds light on the fact that productivity contributes the least to predict the failure of newly-founded firms regardless of variable groups. At this stage of understanding, we believe that productivity dominance among other financial ratios is associated with industry peers and how well similar companies are doing. From the perspective of mathematical explanation, assets in the denominator start to evaporate very quickly because of accumulated losses. Therefore, it is difficult to understand the probability of bankruptcy by only looking at the productivity ratio.

The present study confirmed the findings of the prediction capability difference between the first and last year's reports. Planned comparisons revealed that using last year's and both year's reports made a significant difference in comparison to using the first year's reports only. In contrast, the accuracies obtained by using last year's reports were slightly lower compared to when using both year's reports. Whereas (Fuertes-Callén et al., 2020)received a maximum of 69.9 % accuracy in neural networks, our results provided 65 % and 64.1 % accuracies in neural networks for last year's and both year's reports, and they used more financial and non-financial variables which can increase model's accuracy. In line with one sectoral analysis, Fuertes-Callén et al. (2020) have used startup firms from high-tech and knowledge-intensive services industries identical to our 2 sectors in table 3. As stated before, their maximum accuracy (69.9 %) was provided by neural networks, whilst based on our sector-wise analysis, the results lead to a similar conclusion where the prediction accuracy of high-tech newly founded startup firms was equal to 69.8 %. However, both (first and last year report together) variable groups provided higher accuracy (71.9 %) than what Fuertes-Callén et al. (2020) had obtained. When comparing our results to those, it must be pointed out that we used bulk data from 33 countries with 27,533 observations while they used only 6,176 Spanish companies. In addition, we considered first and last year reports because first report can equal to the last report for younger firms owing to bankruptcy in early operation periods. Moreover, the business models in various sectors differ from each other due to the financial ratios calculated from financial reports because high-tech newly-founded startup companies, in this sense ,are provided with the highest accuracy and prediction capability, as they necessitate significant investments to operate in fixed assets altering the financial statements in different ways.

On the other hand, compared to our result using last yearyear's reports, the accuracy of logistic regression by Ciampi (2015) is much higher, resulting in 80.9 % overall for failed and non-failed firms, while our classification accuracy was 61.8 % for logistic regression and 64.1 % for neural networks. In other research, McKee and Greenstein (2000) obtained 42 % accuracy for failed firms of the first-year report in logistic regression, while our score for the same model exceeded approximately eight percentage points. However, the neural networks in their research outperformed ours. It is difficult to explain such results within the context of accuracies because of various factors such as train-test split, data size, and variables used.

In the case of the first-year report, some studies have similar results to ours. For example, Lukason and Käsper (2017) used logistic regression to predict startup failure funded by the government in the first and second-year reports of the foundation. They acquired an overall 63.8 % and 67.8 % for the first and second year respectively while our accuracy for the first-year writing is 59.8 % for logistic regression and 58.8 % for neural networks. However, one interesting fact is that our accuracy for non-failed firms was higher than theirs. Both studies used newly-founded firms; thus, the first-year report is equal to last year's report for very young bankrupt firms because there is only one available report to predict startup firms with early bankruptcy. Therefore, we can account for last year's report accuracy (64.1 % for neural networks),which slightly outperformed their accuracy. On the other hand, the causes of differences between our results might be related to the sectors used in the data. Thus, Lukason and Käsper (2017) considered government-funded startup firms in Estonia. It created a bias for comparison because of the size of the data and factors affected by the government. Hence, government-funded startups obtain more incentives in terms of the legal environment, investment fluctuations, and the probability of bankruptcy compared to private startups in different countries. Laitinen (1992) also provided a range between 25 % and 40 % for misclassification rates similar to ours. According to his assumption, there is a likelihood that even though the financial state was quite solid in the initial year, that worsened afterwards, which ended up with lower prediction accuracy for models using only initial year data. Therefore, the models cannot solely rely on the first year's report to obtain high accuracy. The financial state of the firms in different stages after their foundation can develop the accuracy of the model pretty much in a good way. Huyghebaert et al., 2000correctly predicted 79 % of failed and 88 % of non-failed firms by applying financial ratios and fund flow variables of one year before bankruptcy in the GNW model. In contrast, our models provided an overall 75.3 % and 71.6 % for non-failed firms based on last year's logistic regression and neural networks reports, respectively. Although the predictive capability of our model is lower than expected, accuracy is not without worthiness. They used funds flow variables that positively affected the accuracy level because it was obtainable in the small sample size. However, we cannot get fund flow variables in our prediction model because of the extensive number of observations. Admittedly, our model would achieve higher accuracy in the classification matrix if type I error increased by classifying newly-founded startups as non-failed. However, it should be taken into consideration that according to Altman et al. (1977), making a type I error is an pproximately 35 times more costly process for investors, banks and financial institutions than making a type II error. On the other hand, Pompe and Bilderbeek (2005) created prediction models to compare accuracies based on young and old firms' last annual reports, and their study confirmed the findings that it was more challenging to predict the bankruptcy of young firms compared to old firms. While maximum accuracy for newly founded startup companies was 65 %, their model came up with higher accuracy (77 %) for young firms using the stepwise selection method for the neural networks technique. A difference between these accuracies can only be attributable to the age of selected companies. Pompe and Bilderbeek (2005) considered young firms up to 8 years old to use in the prediction model. In our study, we only considered the first five-year time span of newly founded startup firms. Therefore, accuracy for older firms alters the results towards higher accuracy according to their hypothesis mentioned above.

It is essential to highlight the fact that several factors also affect the capability of prediction in different countries. Thus, the number of failed firms can lead to bias in models for full population and sector prediction. We took five countries according to the highest number of failed firms to forecast failure in an individual country. Accuracy for Italy, which provided the most outstanding results among the selected countries with a of maximum 71.2 %, was outperformed by Altman et al.

(2017). However, when comparing our results with theirs, our model obtained identical results to theirs for Great Britain. A popular explanation of the differences is that insolvency legislation and compulsory liquidations alter for every country, indirectly influencing the prediction of bankruptcy in newly founded startup firms. In addition, the trade-off of voluntary liquidation in each country varies due to a lack of an obligation to submit reports every year, which makes it more challenging to calculate financial ratios. In other words, there might be missing values in the data set, which result in different accuracy scores across countries and business areas.

The findings lead to some practical implications, which are quite interesting for further consideration. There should be optimal policy measures that can help startup firms to prevent from going bankrupt, and these can be carried out through external financial support. If there seems to be a negative tendency in cash flow, not much money should be invested in the enterprise. Depending on the different stages of fa irm's cycle, Lukason and Laitinen (2019) suggests that profitability is the most important one for predicting the failure of startup-based firms. However, both yearly and accumulated profitability are necessarily required for consideration, followed by dynamic alteration of profitability over the years. These are the leading indicators to track the potential cash flows. It is necessary to observe that the firm is making a reasonable profit and a positive cash flow in the initial years. In the very beginning, startup firms might need consultancy that can help them follow the business process effectively. That would also give them the chance to get support from financial institutions and relevant policy measures being in place. From the model we created, investors can assess the financial status of startups based on their financial accounting. A freshly formed company with solid financial indicators is highly likely to continue running compared to one experiencing difficulties. However, this does not mean that the sole priority should go to financial information, as other non-financial characteristics might have some reasonable level of usefulness for indicating the likelihood of bankruptcy.

6 Conclusion

The main focus of the research was to predict the failure of European startup firms and compare the contribution of the financial reports by using logi stic regression and neural network techniques. The data we used in the prediction was taken from the ORBIS database and consisted of 27,533 (22,576 survival and 4,957 failed firms) observations which belonged to high technology, medium high technology and knowledge-intensive service sectors according to Eurostat indicators. The variable groups used in the models were last, first and both (last and first together) financial reports of the startup, which incorporates four financial ratios per variable group. Firstly, we found that profitability contributed relatively more to a bankruptcy prediction than the other applied ratios. Secondly, the main finding is that the previous studies tended to develop the models to avoid a potential failure by using the same logic in prediction modelling, however, researchers did not focus on using both variable groups (last and first year) to compare the accuracies of models against what was obtained from the first and last years' reports separately. Importantly, our results provide evidence for variable groups that the output derived from the last year performed better than that of the first year's accuracies.

Moreover, the additional effort which led to assurance follows from the fact that the last year's report provided a reasonable accuracy even though there was no significant difference between last and both years' reports. In addition to the whole population, our results in last year's report are also broadly consistent with each sector and country with a more substantial number of failed firms. In terms of country-wise diagnostics, we checked our variable groups for countries with a higher number of failed firms because higher ones dominate over less failed firms. Thus, it undoubtedly impacts the accuracy, even in a small percentage. Regarding the sectors, we obtained similar results in terms of the financial reports. One interesting finding is that high-technology firms provided more accurate results than medium high-tech and knowledge-based intensive services firms. We concluded that last year's reports provided more precise results than the first year's reports for five leading countries. In summary, this paper argued that last year's and both years' reports produced noticeably higher results than the first year's reports, whilst the accuracies of both years' reports did not differ reasonably from last year's reports alone.

There might be some limitations that can impact the model's accuracy in terms of both additional variables usage and non-financial information. Also, the prediction of bankruptcy would be somewhat tricky for newly-established firms that showed not moderately good performance over early operation. As the age of the firm increases, the failure process tends to become more visible, so it would be relatively easier to detect what kind of causes lead to failure (Lukason et al., 2016). As a leading example, the firm whose report is only available for the first year does not produce reliability for accuracy. It would be fair to say that considering such non-financial information would develop the model's accuracy at some level. Focusing on the firm-specific features would be sensible to examine the likelihood of survival of a given firm. Another potential improvement can be observed by having a more significant number of observations that can potentially develop the model. Alternatively, beyond the industries used in our study, it would make sense to apply the model to additional sectors and countries.

Future investigations are necessary to validate the conclusions drawn from this study. Additional research would be helpful in the future if such a study would examine a more significant number of countries and how accuracy changes across those countries. There might appear some follow-up questions explaining the primary causes of failure for a particular country. Also, many variables can be used in the model after realising the importance of variables and their contribution to the model for a higher classification rate.

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„Euroopa iduettevõtete ebaõnnestumise prognoosimine“

Magistritöö eesmärk on prognoosida Euroopa riikide idufirmade ebaõnnestumist nende finantsaruannete põhjal. Idufirmana on käsitletud uuringus äsja asutatud kõrgtehnoloogilist ettevõtet.

Varasemad uuringud on käsitlenud ettevõtete ebaõnnestumise ennustamist erinevate statistiliste ja masinõppemeetodite abil kasutades majandusaruannetest tuletatud finantssuhtarve, kuid osutus, et finantsteavet ei olnud hiljuti asutatud ettevõtete kontekstis lihtne rakendada, kuna uuritud ettevõtted olid oma elutsükli erievates etappides. Varasemates uuringutes ennustasid teadlased pankrotti nii esimese kui ka viimase aasta raamatupidamisandmete põhjal eraldi, kuid meie oma analüüsis kaasasime ka esimese ja viimase aasta aruannete andmeid samaaegselt, et võrrelda eri aastate finantsnäitajate kasutamisega saadud ennustustäpsusi.

Empiiriline uuring keskendus 2015. aastal asutatud 27 533 ettevõttele 33 Euroopa riigist, neist tegevuse esimese viie aasta (2016–2020) jooksul 4957 ettevõtet pankrotistusid ja 22576 ei ebaõnnestunud. Kuna varasemad uuringud on näidanud, et finantssuhtarvud on olnud edukad ettevõtete pankrotistumise ennustamisel, siis keskendusime likviidsuse, kasumlikkuse, tootlikkuse ja maksevõime suhtarvude kasutamisele, kasutades esimese ja viimase aasta aruandeid kui ka mõlemaid koos, ning rakendades logistilise regressiooni ja närvivõrkude tehnikaid. Tulemustest ilmnes, et üksikute finantssuhtarvude panused ettevõtete pankrotistumise ennustamisse erinesid üksteisest oluliselt.

Meie tulemuste põhjal andsid nii esimese kui ka viimase aasta aruandeid ja ainult viimase aasta aruandeid kasutanud mudelid parema ennustustäpsuse võrreldes esimese aasta andmeid kasutanud mudeliga, samas märgatavat erinevust kahe esimese mudeli ennustustäpsuses ei olnud.

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