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Accounting-based modelling for bankruptcy prediction for privately-held small and medium manufacturing companies: the case of Italy

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TABLE OF CONTENTS

Introduction 4

CHAPTER 1. THEORETICAL BACKGROUND 7

1.1 Examination of manufacturing SMEs in Italy: the issue of bankruptcy...................................7

1.2 Definition of bankruptcy 9

1.3 Bankruptcy prediction: Accounting-based models...10

1.4 Bankruptcy prediction: Tools 19

CHAPTER 2. METHODOLOGY 23

2.1 Statistical methodology 23

2.1.1 Logit specification 23

2.1.2 Models specification...24

2.1.3 Prediction quality assessment..27

2.2 Sample collection 29

2.3 Sample description 32

CHAPTER 3. RESULTS AND MANAGERIAL IMPLICATIONS...35

3.1 Results 35

3.2 Limitations...42

3.3 Managerial Implications 43

CONCLUSION 45

LIST OF REFERENCES...47

APPENDIX 59

Appendix 1. Correlation matrix...59

Appendix 2. Youden index 60

INTRODUCTION

The topic of bankruptcy prediction is one of the central issues in the world of finance (Mselmi et al., 2017). When a firm is not able to meet its obligations and has no other way but to declare bankruptcy, the company is not the only actor who suffers. Bankruptcy is definitely an undesired event for all the groups of stakeholders. In such circumstances, shareholders are usually left out without the invested money, suppliers are not paid for the goods provided, creditors are forced to write off bad debts. Moreover, employees are relieved from employment and customers cannot buy products they love or need anymore.

As mentioned by Bal (2016), bankruptcy is often a long-term process that starts several years prior to the undesired event and the earlier companies gain insights on their position, the more chances they have to rectify the situation and avoid bankruptcy declaration. Most of the time, it does not happen the way that companies are operating and, suddenly, declare bankruptcy. Before a company files bankruptcy, it has an ability to get additional financing from banks. However, it is also a challenging task. After the global financial crisis in 2008, Basel Committee of Banking Supervision (BCBS) issued the third edition of Basel requirements for banks, that imposed more restrictions on banks in terms of leverage and liquidity in order to decrease the risks for banks and make them not so vulnerable to large financial instabilities (Bank for international settlements, n.d.). As a result, banks are now reluctant to give additional loans to companies that are in danger. That is the reason why it is necessary for companies to recognize the signals of upcoming problems before it is too late.

First attempts to address the issue have been made in 1930th (Bureau of business research, 1930). Since then, researchers have been trying to elaborate on a methodology that will be capable of making accurate predictions of bankruptcy several years prior to the event. If working, such methodologies could be used by creditors for assessment of companies, by suppliers and buyers to assess risks and by companies themselves to foresee their default and make an action in case there are impending problems. The first model that came into place was introduced by Beaver (1966). Later on, there has been a surge in the development of various models with the use of different statistical techniques and indicators. Much attention has been put to the research of Ohlson (1980), Zmijewski (1984) and Altman (1968), since the models introduced in these papers have proved to be effective for the task of bankruptcy prediction across several countries. However, the note should be made regarding the adaptability of every bankruptcy prediction model to varying conditions. There is no unique bankruptcy prediction model that will suit all the countries, economic conditions and industries. When comparing the effectiveness of the same model on varying circumstances, researchers tend to come to different results. Hence, the majority of bankruptcy prediction models produce varying classification accuracy rates for different samples. The contradiction has been found in the research of Du Jardin and Séverin (2012), Tsai and Cheng (2012), Bansal & Kashyap (2020) and Seto (2022). The difference in results creates the need to find an appropriate model for each country, industry and economic situation separately.

The research will focus on the case of bankruptcy prediction of privately-held small and medium manufacturing enterprises operating in Italy. The choice has been made in favor of small and medium enterprises (also referred to as SMEs) due to the fact that SMEs account for 99% of Italian service and industrial firms (OECDiLibrary, 2020). At the same time, the percentage of vulnerable companies and companies at high risk of bankruptcy category among SMEs was equal to 46,5% of all SMEs as of 2020, which is a 57% increase as compared to 2019 (Statista Research Department, 2021). Hence, the issue of bankruptcy prediction in Italy is of paramount importance.

Before considering the research gap that has been formulated after detailed literature review, it is worth mentioning two factors. First, there are numerous models that were built by researchers to forecast bankruptcy; however, the primary emphasis of these models is on the application to public companies. At the same time, the importance of bankruptcy prediction for private companies cannot be underestimated but the literature researching this topic is quite limited (Matenda et al., 2021). It especially refers to Italian SMEs, where the number of private companies is prevalent (OECDiLibrary, 2020). Second, the business environment is different across countries, which results in the effectiveness of some models, and at the same time total uselessness of other models. Platt and Platt (1990) confirm that the differences in economic environment are likely to change the relationship between dependent and independent variables, the range of independent variables and the relationships among the independent variables. In addition, Grice and Ingram (2001) state that structure of the models changes over time, as well as the importance of certain ratios, which requires the re-estimation of coefficients of the ratios in models. Summing up all the factors mentioned above, **a research gap** is formulated as follows: there is limited research regarding the bankruptcy prediction model suitable for privately-held small and medium manufacturing companies operating in Italy in current economic and business conditions.

Current research aims at addressing the issue of bankruptcy prediction for privately-held manufacturing SMEs operating in Italy. The **research question** is “What is a more accurate bankruptcy prediction model for privately-held manufacturing SMEs in Italy”? Hence, the **research goal** is formulated as follows: To determine the model that accurately predicts bankruptcy for privately-held manufacturing SMEs operating in Italy. Hence, the **research object** is privately-held manufacturing SMEs operating in Italy. **Research subject** is defined as financial indicators and models that are significant for bankruptcy prediction of manufacturing SMEs operating in Italy.

The research goal is augmented by several **research objectives**:

1. To study the notion of bankruptcy, as well as the main models and methods of bankruptcy prediction.
2. To assess the performance of the existing bankruptcy prediction models on the sample of privately-held manufacturing SMEs operating in Italy.
3. To formulate a combined model for bankruptcy prediction and assess its performance on the sample of privately-held manufacturing SMEs operating in Italy.
4. To compare the performance of models and choose the most suitable one for the case of bankruptcy prediction for privately-held manufacturing SMEs operating in Italy.

The research is **empirical** and **quantitative** in nature and relies on the **secondary data** obtained with ORBIS database (Bureau van Dijk, n.d.). The statistical software used in the research is Rstudio. The theoretical and methodological parts of current research lean on the research of Ohlson (1980), Altman (1983) and Zmijewski (1984) that developed models combining lists of financial indicators which predict bankruptcy with high classification accuracy; on the research of Seto (2022) and Viciwati (2020) that made a comparison of well-established models; on the research of Bellovary et al. (2007), Kovacova et al. (2019) to identify the most relevant variables for bankruptcy prediction. The thesis also relies on the research of Gilenko et al. (2013), Tsai & Cheng (2012), Min & Jeong (2013) for data analysis.

The research is organized as follows. Chapter one provides a comprehensive literature review on the notion of bankruptcy, methods and models used to predict bankruptcy, specifics of bankruptcy prediction for private companies and Italian companies, in particular. Chapter two introduces methodological basics of research including the process of new model development, procedure of data collection and cleaning and sample description. Chapter three presents results of the research and makes conclusions regarding the predictive abilities of the models and suitability of the models for the context of research.

CHAPTER 1. THEORETICAL BACKGROUND

1.1 Examination of manufacturing SMEs in Italy: the issue of bankruptcy

The current research is focused specifically on the private small and medium manufacturing enterprises operating in Italy. Hence, it is first worth considering a general overview of the country and industry and confirm the relevance of the problem of bankruptcy in the defined context.

Italy is one the countries in the European Union which can boast a large landscape and expansive populace. According to Eurostat (2023), Italy has the seventh largest surface area and third largest population when compared to all countries of the European Union. As of 2022, the population of Italy was equal to 59 030 133 (Eurostat, 2023). At the same time, the number of enterprises operating in Italy was equal to 4 427 307, as of 2020 (I.stat, 2021). The quantity of companies can be seen as considerable, since it accounts for 7,5% of the total population in Italy and is deemed to have the largest number of non-financial enterprises in the European Union (European Commission, 2022). The figure is significant not only in terms of comparison to the number of enterprises by country, but also from the perspective of the whole European Union. The total number of companies operating in the European Union as of 2020 was equal to 22 567 303 (European Commission, 2022), which means that companies operating in Italy account for more than 19,6% of the overall figure.

When diving deeper into the examination of enterprises operating in Italy, several points should be highlighted. According to the European Investment Bank report prepared for the European Investment Advisory Hub in 2021, small and medium enterprises (also referred to as SMEs) play a major role in the Italian economy and account for 99,9% of all companies operating in Italy. At the same time, SMEs operating in Italy provide about 80% of employment and 70% of gross value added (European Investment Bank, 2021). Hence, SMEs are an exceptionally meaningful part of the Italian economy.

Moving on to the ownership structure, there is a marked prevalence of private companies operating in Italy. According to CEIC, one of the established and well-known data providers, the number of listed companies in Italy varied from 459 000 to 464 000 (CEIC, 2023). Taking into account the total number of companies in Italy, it can be summed up that the majority of companies in Italy are private, with slightly more than 10% being publicly listed ones. Hence, privately-held manufacturing SMEs play a crucial role in the economy of the country and stability of operations of these businesses is of great interest for Italy.

Keeping in mind the importance of privately-held SMEs operating in Italy, it is paramount to consider the industries in which Italian companies operate and the share they bring to the GDP of Italy. According to the International Monetary Fund (2023), from 2017 to 2019 the GDP of Italy has been rising slightly by 0.93% and 0.48%, respectively. As of 2020 the GDP dropped significantly by 8.98% due to the COVID-19. However, it has risen again in 2021 by 6,99% and as of the end of 2022 increased by 3,68% and exceeded the GDP of the previous five years (International Monetary Fund, 2023). Besides the fact the Italian economy has been hurt by the event of COVID-19 as reflected in the GDP of the country, only two years required to return the measure to before the COVID-19 state.

Among all the companies operating in Italy, more than a million of companies operate in the wholesale and retail trade industry, about 840 000 companies are in the industry of professional, scientific and technical activities, circa 520 000 companies are involved in the construction and 367 358 operate in manufacturing industry, as of 2021 (I.stat, 2023). Hence, the manufacturing companies are the fourth largest sector employing over 3 747 938 people (I.stat, 2023). Being the fourth largest industry in Italy, the manufacturing industry accounted for 16,64% of total GDP of the country, as of 2021 (EIU, 2023). Considering the impact of COVID-19 on the manufacturing sector in Italy, it is possible to highlight the following: since February 2020 the industrial production started diminishing and achieved the highest 44.3% drop in April 2020 as compared to the previous year. However, since April 2020, the industrial production slowly started to recover and in April 2021 achieved a 74,1% growth as compared to April 2020 (Statista, 2021). As concluded by I.stat (2021), the manufacturing industry started to demonstrate a positive trend after COVID-19 pandemic as compared to 2015 base year since March 2021.

Coming to the problem of bankruptcy in Italy, one can highlight the importance of the topic. The situation in the world is quite unstable, starting from COVID-19 in 2020 and the following gas crisis (Falavigna & Ippoliti, 2022) create the need to address the issue of bankruptcy in every country. Recent statistics regarding the expectations of business insolvencies shows that Italy had ninth highest expectations of business insolvencies all around the world equal to 8 990, as of 2022 (Global insolvency report, 2022) which is a ground to assume that the issue is of paramount importance for Italy. Meanwhile, the Statista Research Department (2021) presents the results on default risks for small and medium enterprises in Italy that demonstrate that at least 29,6% of all SMEs in Italy have been either in the vulnerable or risky category for the period from 2016 to 2020. Despite some variation, it is possible to make a notice on the considerably increased number of risky and vulnerable companies in 2020 totaling to 46,5%. The detailed description of trends in the field of riskiness of Italian SMEs is provided in Table 1.

Table 1. Default Risk Distribution among SMEs in Italy

Year \ Status	Safe	Solvent	Vulnerable	Risky
2016	24%	37%	28,9%	10,1%
2017	25,8%	37,8%	25,3%	11%
2018	28%	37,9%	24,6%	9,5%
2019	32,6%	37,8%	21,2%	8,4%
2020	14,5%	39%	30,2%	16,3%

Source: Statista research department. (2021). Default risk distribution of small and medium enterprises (SMEs) in Italy from 2016 to 2020, by risk category. Retrieved March 26, 2023 from https://www.statista.com/statistics/825040/default-risk-distribution-of-small-and-medium-enterprises-smes-by-risk-category-in-italy/?locale=en

To sum up, the topic of bankruptcy is of paramount importance for every country and firm, however, the issue is especially vital for companies operating in Italy, particularly, privately-held manufacturing SMEs. As has been observed, the majority of companies operating in Italy are SMEs, with the domination of private companies in the ownership structure. At the same time, the manufacturing sector is the fourth largest sector that brings around 16% to the overall GDP of Italy and can be considered as one of the most important for the economy of Italy. With this information, the extent to which SMEs are in the group of risk creates the necessity to approach and address the problem of bankruptcy prediction in Italy.

1.2 Definition of bankruptcy

Before the review of prior research in the field of bankruptcy prediction is made, it is crucial to address the issue regarding the definition of bankruptcy. When making research on bankruptcy prediction, the undesired situation which companies enter is often referred to as failure, default or bankruptcy without the commitment to the only definition.

Since the research is conducted for companies operating in Italy, the first notion to be presented refers to the Italian legal definition of bankruptcy. According to the Italian Insolvency Act issued in 1942, Chapter 5 “The entrepreneur who is in a state of insolvency is declared bankrupt. The state of insolvency is manifested by failures to comply or other external events that demonstrate that the debtor is no longer able to regularly fulfill his obligations” (Altalex, 2023).

The definition of bankruptcy in literature, however, is not unique and straightforward. According to Balcaen & Ooghe (2006), the definition of bankruptcy is arbitrary and differs from one research to another. Altman (1968) considered a firm as bankrupt only if it is legally defined as bankrupt. Contrary to Altman (1968), Aliakbari (2009) defines bankruptcy as inability of a person, business or firm to repay its outstanding debt.

It is often the case that researchers use the word “failure” to refer to the situation of bankruptcy. As highlighted by Karels and Prakash (1987), there is also a diversity of ways researchers define failure. Despite the fact that definitions vary, the most used and widely accepted one refers to the ultimate failure (Bellovary et al., 2007), meaning that company has stopped its being. In this sense definitions of Bellovary et al. (2007) and Altman (1968) are similar. Another way to talk about bankruptcy is tightly connected to the word “financial distress”. When considering financial distress, there are several ways of presenting it. The research of Laitinen (1994) employs the notion of financial distress and considers a company as financially distressed if it has cash insolvency, while research of Platt and Platt (2002) includes financially distressed, but not yet bankrupt firms in the sample, meaning that the two notions are separated.

To avoid any ambiguity connected with the use of multiple meanings, research will use only word bankruptcy, which will define a firm as legally bankrupt and no more existing, which is consistent with the notion introduced by Altman (1968).

1.3 Bankruptcy prediction: Accounting-based models

Since Beaver (1966) made a first breakthrough in terms of bankruptcy prediction modeling, there has been a surge in the number of bankruptcy prediction techniques and models. The models differ in various senses. The thing that unites the majority of models refers to the presence of a dependent variable that is usually a dichotomous variable tied to the title denoting whether the company is bankrupt or not and a certain number of independent variables (Altman, 1968). According to Bellovary et al. (2007), the number of independent variables used in the models of researchers achieved 57. Established models are usually made for certain purposes and some are intended for the narrow field of application only (Bellovary et al., 2007). For example, the model of Altman (1968) is designed solely for manufacturing listed companies, while the model of Wang (2004) was built specially for companies operating in the internet industry. Regardless of dependent and independent variables used in the research, techniques employed for the research differ as well. The early studies focused on univariate and multivariate discriminant techniques to predict bankruptcy. However, the progress in the development in the field of statistics allowed the use of logit and probit techniques, as well as neural networks (Bellovary et al., 2007).

All in all, there exists a classification of bankruptcy prediction models. Bankruptcy prediction models can be largely divided into the two main groups: parametric and non-parametric ones (Singh & Mishra, 2016). Parametric models refer to the classical statistical models of both univariate and multivariate nature with large focus on early symptoms of failure and employment of standard modeling procedures (Aziz & Dar, 2006). Parametric models are further divided into accounting and market approaches. Accounting-based models tend to apply information from the financial statements of companies and various ratios composed from the information from financial statements, while market-based models tend to use the data on stocks and market variables for forecasting (Singh & Mishra, 2016). Non-parametric models, in turn, focus largely on the use of machine learning techniques and include hybrid models, artificial neural networks and hazard models (Singh & Mishra, 2016). Due to the fact that this research is focused on private companies which are not listed, hence, do not possess market information (e.g. on stock prices), the attention will largely be put on accounting-based models.

The history of the development of bankruptcy prediction models dates back to the early 1930th (Bellovary et al., 2007). First attempts to predict bankruptcy were not concerned with models themselves. On the contrary, researches developed by Bulletin of Business Research (1930), FitzPatrick (1932), Smith and Winakor (1935) focused on the comparison of various ratios in order to develop the list of the most useful ratios that would differ for bankrupt- and non-bankrupt firms and, consequently, identification of signals of financial weakness and potential default of the companies.

Based on the findings of those mentioned above, Beaver (1966) introduced the first parametric model of univariate nature. The researcher made a comparison of 30 ratios among 158 non-random observations that were classified into two groups: 79 failed and 79 non-failed firms. Then, the predictive ability of each ratio was tested. The model was able to make predictions with up to 92% accuracy in a one-year horizon. However, as criticized by Altman (1968), the ratio analysis is susceptible to faulty interpretation and pays attention only to individual signals of impending problems. Overall, the univariate discriminant analysis where ratios were tested one at a time (Beaver, 1966) laid the foundation for development of multivariate analysis.

The next breakthrough in the field of parametric models was made by Altman (1968). In Altman's model employing multivariate discriminant analysis (also referred to as MDA), the dependent variable was introduced in a qualitative form as a binary variable with possible values of either bankrupt or non-bankrupt. Then, each observation was classified as bankrupt/non-bankrupt. Independent variables were chosen among 22 ratios based on their predictive accuracy, statistical significance and intercorrelation between the variables. Overall, five most important ratios of leverage, liquidity, solvency, profitability and activity were chosen and a five-factor function was built. Z-score was used to predict the bankruptcy of the firm: if a score was under 1.8, the company was likely to face bankruptcy, while the score over 3.0 was a reliable signal of the company's health. The model performed quite well (95% accuracy) in the one-year horizon, however, the accuracy decreased dramatically in the second and third years before the bankruptcy (accuracy of 72% and 48% respectively) (Altman, 1968).

However, the feature of the original Altman model (1968) is that it was built specifically for public companies operating in the manufacturing industry, since it uses market value of equity to total liabilities ratio as one of the predictors. The market value of equity is hardly obtained for private companies, which was the main reason for the introduction of the new model of Altman (1983) that was designed for privately-held manufacturing firms. The main difference to the previous models refers to the fact that the Altman Z'-score model substitutes the market value of equity to the book value of equity (Altman, 1983).

Later on, Altman (1993) elaborated on the Z''-score model that can be used to predict bankruptcy in other non-manufacturing industries and in emerging markets. The Z''-score model is different from previous ones in that it excludes the fifth ratio of sales to total assets. According to Altman (1993), the exclusion of the ratio results in the elimination of the industry effect which appears when industry sensitive variables are included. Overall, the model introduced by Altman in 1983 has quite high predictive accuracy of 90.9% for bankrupt firms one year prior to bankruptcy and 97% accuracy for non-bankrupt firms.

Altman's models have gained considerable attention and gave rise to the continued research in this field. The research of Singh and Mishra (2016) employed the original Altman model (1968) and re-estimated the coefficients of the model on the sample of Indian companies. The original Altman Z-score model has brought the overall classification accuracy of only 67.1%, while the re-estimated Z-score model illustrated the strong classification accuracy of 96.9%. In similar manner, the research of Begley et al. used the original Altman model (1968) to the sample of companies that went bankrupt in 1980th and re-estimated the coefficients of the model which resulted in the overall accuracy rate of 78.4%. Grice and Ingram (2001) tested the generalizability of Altman Z-score model and were able to achieve the accuracy rates of 93,8% for the sample of companies that went bankrupt in 1985-1987. The research of Range et al. (2018) collected the data for Kenya sugar companies via questionnaires and financial statements to employ Altman Z'-score model and proved its applicability for a given setup. Altman et al. (2017) using a considerable sample of 5,832,521 companies found out that the Altman Z''-score model is suitable for bankruptcy prediction in an international context with an accuracy rate of over 75%. Finally, the research of Rim and Roy (2014) has found out that the Altman (1983) model can serve as a benchmark to classify the firms into bankrupt and non-bankrupt. Overall, all the three Altman models designed for public manufacturing companies, private manufacturing companies and non-manufacturing companies prove their ability to achieve a high classification accuracy.

Based on the previous works done by Altman (1968), Moyer (1977), Wilcox (1973) etc., Ohlson (1980) elaborated on a new approach to bankruptcy prediction using logit models. Conditional logit analysis, in turn, is able to avoid problems that appear when multivariate discriminant analysis is employed - no assumptions about distribution of predictors should be made as well as statistical significance could be obtained for all the independent variables (Ohlson, 1980). Ohlson (1980) proposed the logit model with four statistically significant factors represented by nine financial ratios that have a bearing on the prediction of bankruptcy – these are size, financial structure, current liquidity measures and set of performance measures. The cutoff point in the research of Ohlson (1980) was equal to 0.38. The point was chosen in the manner that minimized Type 1 and Type 2 errors. If the probability was below 0.38, it meant that the company had been predicted to enter bankruptcy, while the probability above 0.38 indicated that the company was not likely to face bankruptcy. Overall, the logit model was able to predict bankruptcy with 96% accuracy for both one and two years prior to the default (Ohlson, 1980).

The model of Ohlson (1980) has also obtained wide recognition among researchers. Grice and Dugan (2003) assessed the model of Ohlson and obtained the low classification accuracy of 30.1% which served as a reason for model re-estimation. The re-estimated model of Ohlson was able to classify 93.7% of observations correctly. Analogously, Oz and Sigma-Muran (2018) have come to the conclusion that the original Ohlson model should be re-estimated and have come up with classification accuracy of 94.03%. Finally, acting with the same methodology, Salim (2021) was able to achieve the classification accuracy of 90,91% on the Indonesian companies operating in the coal mining industry.

A considerable contribution was also made by Zmijewski (1984), who elaborated on the probit model using three financial ratios. The research criticized choice-based samples for being non-random and causing biased parameter and probability estimates. In his paper, Zmijewski (1984) compared estimates from probit model and adjusted probit model to demonstrate the presence of bias related to choice-based samples and choice of observations only with complete information. However, the researcher proved that the presence of bias does not significantly affect the statistical inference and does not have a bearing on the tests that classify firms as bankrupt or non-bankrupt (Zmijewski, 1984). The estimation sample in the paper used only 40 bankrupt and 800 non-bankrupt firms, while the sample for prediction contained 41 bankrupt and 800 firms that are not bankrupt. Zmijewski (1984) described the probability of bankruptcy as a probit equation where a firm was considered as bankrupt if an underlying response variable was more than 0. The model that was built by Zmijewski (1984) used the three ratios of productivity, leverage and liquidity. Similar to the model of Ohlson (1980), the model gave the result of classification as a probability with the value between 0 and 1. The cut-off value was chosen to be 0.5. It means that all companies with probability equal or higher than 0.5, were considered as bankrupt firms, while companies with probability less or equal to 0.5, were not referred to as bankrupts. Overall, the model achieved a classification accuracy of 99% (Zmijewski, 1984). Later on, the Zmijewski model was applied and re-estimated in the research of Grice and Dugan (2003) with the classification accuracy of 98.2% and Oz and Sigma-Migan (2018) with the overall classification accuracy of 94.14%.

There are other models that have been built by researchers to predict bankruptcy. These models include the models of Springate (1978) and Grover (2001). The Springate model (1978) was built based on the employment of four ratios of liquidity, profitability and efficiency, while the model of Grover (2001) uses return on assets, working capital to total assets and profit before interest tax to total assets as financial indicators defining bankruptcy. However, the scope of application of these models is much smaller and the accuracy with which the models predict bankruptcy is lower, as compared to Altman's models, models of Ohlson (1980) and Zmijewski (1984). The research made by Salim (2021) applied the models of Springate (1978) and Grover (2001) in comparison with the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) and has come to conclusion that the models of Springate and Grover demonstrated the lowest prediction accuracy of only 63,63% and 81,82%, respectively, on the sample of companies listed on Indonesian stock exchange, while models of Altman (1968), Ohlson (1980) and Zmijewski (1984) were able to classify the data with accuracy of 90.91% for the first two models and 86.36% for the latter one. Aprilia et al. (2022) have demonstrated the predictive ability of Springate and Grover models to be only 50% and 83%, respectively.

Nowadays there are still no unique conclusions regarding the best accounting-based model for the prediction of bankruptcy. Extensive research has already been done to find out the unique model that would fit for every case, however, results differ among researchers. Research on Indian organizations conducted by Bansal & Kashyap (2020) demonstrated the higher predictive ability of Ohlson's model, while the research of default prediction during and after COVID-19 presented by Seto (2022) demonstrated clear superiority of Altman's model. Avenhuis (2013) made a comparison of Ohlson, Altman and Zmijewski models for Dutch companies and came to the conclusion that models of Zmijewski and Ohlson are the best ones with forecasting power of 87.7% and 93.8%, correspondingly. Researches made by Begović et al. (2020), Viciwati (2020) also prove the prevailing power of Zmijewski model, while Sharma (2020), Karamzadeh (2012) talk in favor of Altman's model. However, results show that all the three models are able to report high accuracy. It is also proved by the results of Grice and Dugan (2003), Berzkalne and Zelgalve (2013), Alodia (2016). The high accuracy rates of prediction serve as the justification of the relevance of usage of the models of Ohlson (1980) and Zmijewski (1983) for the current research that is conducted on the sample of Italian companies.

To sum up, the application of Altman's models, models of Zmijewski (1984) and Ohlson (1980) is the most widespread. Meanwhile, the application of the mentioned models to the case of bankruptcy prediction under various countries, economic and business conditions has proved to bring satisfactory results in terms of predictive accuracy. Hence, it is of great interest in current research to check whether these models will perform as well as in the other research on the sample of privately-held manufacturing SMEs operating in Italy in the most recent period. The research will consider the models of Ohlson (1980) and Zmijewski (1984). Among Altman's three models the research will apply the model that was designed specifically for privately-held manufacturing enterprises (Altman, 1983), as it is consistent with the research object identified in the paper.

While some researchers tend to test the models introduced in the first section and adapt or test them to circumstances of countries and industries of interest, not less attention is put on the development of models that combine various financial indicators to find the list of variables that most accurately contribute to the task of bankruptcy prediction. The research of Lohmann et al. (2022) used the financial indicators identified in the model of Altman (1983) and combined it with the variables, identifying the industry where the company operates and year to build the GAM1 model. The results have demonstrated that the GAM1 model achieved performance quality of the model, equal to 80%.

Xu and Chang (2009) applied separately and then combined the models of Altman (1968), Ohlson (1980), option-pricing theory with binary variable Keiretsu dependence, which is a unique institutional feature of Japanese banks to check whether the combined model was able to predict bankruptcy for Japanese companies listed on the stock exchange. Results have demonstrated that the combined model performs economically better.

The research of Gupta et al. (2015) explored the set of financial variables and checked its applicability for bankruptcy prediction for separately micro, small and medium enterprises. The research has found out that the majority of financial indicators used in the research, if significant for one category of SMEs, will be significant for bankruptcy prediction for all categories of small and medium enterprises.

Finally, Min and Lee (2005) identified the list of 38 financial indicators and tested them for significance in the task of bankruptcy prediction. The research has come up with only eleven ratios suitable for analysis, including sales to operating assets, income to assets and equity to total assets which brought the bankruptcy prediction accuracy rate of 88% for training sample and 83% for testing sample when the support vector machines (also referred to as SVM) method is applied.

While research introduced above demonstrates how sets of financial indicators are chosen and combined in new models to predict bankruptcy and discover the applicability of these models to certain contexts for public companies, it is also worth taking account of research that has already been conducted for private companies. This narrower field should also be addressed since the focus of this research is on the bankruptcy prediction for private firms. However, the literature on the research of bankruptcy prediction issues for private enterprises is quite limited (Charalambakis, 2014).

The research of Slefendorfas (2016) did not use Altman's model to predict bankruptcy of privately-held companies in Lithuania, however, also relied on multivariate discriminant analysis. In the research, Slefendorfas (2016) used a list of 156 various financial ratios to make predictions. Out of the whole list of ratios used for testing, only nine of them were found to be significant, including the change in sales revenue, operating costs, total assets to total liabilities, total equity to total liabilities, net profit to equity and operating profit to sales revenue. Overall, the model was able to achieve an accuracy rate of 89% .

The paper of Charalambakis and Garrett (2019) researched the bankruptcies of Greek privately-held companies. The model that was built by researchers employed the ratios of profitability, retained earnings to total assets, size, leverage and liquidity and combined them with the indicators of export activity, dividend payout to get insights on whether the latter two have a bearing on the occurrence of bankruptcy. The results were as follows: despite the fact that both of the financial indicators appeared to be significant, the models without export activity and dividend payout variables and with the inclusion of these variables differ only slightly in terms of predictive accuracy.

The research of Papana and Spyridou (2020) used 50 various financial ratios of liquidity, profitability, contribution, efficiency and leverage and compared the performance of various methods on the sample of Greek companies. The results have demonstrated that only nine ratios including total assets to total liabilities, net income to total assets, earnings before interest and tax to total assets and current assets to current liabilities are significant in the particular circumstances of small and medium Greek private enterprises. The research has come to the conclusion that classification accuracy of the model with significant variables was equal to 70,8%.

According to Kovacova et al. (2019), financial indicators are largely divided on activity, liquidity, profitability and debt ratios. The research of Kovacova et al. (2019) was conducted with the purpose to create an overview of ratios used in 103 models built for the countries of the Visegrad group. The research has identified that the most significant and widely used ratios include the current assets to current liabilities, total liabilities to total assets, quick ratio, working capital to total assets and net income to total assets.

The research of Bellovary et al. (2007) has also made a review of bankruptcy prediction models that were considered by various groups of researchers in the period from 1930 to 2007 and also identified the most reliable variables that could be used for bankruptcy prediction. These variables include the net income to total assets, current assets to current liabilities, working capital to total assets and total liabilities to total.

Overall, as can be seen from prior research made for different countries and economic contexts, most of the accounting ratios at least partly coincide with those introduced by Ohlson (1980), Altman (1983) and Zmijewski (1984) and are complemented by the variables of interest. Such a tendency demonstrates that financial indicators used in these three papers remain central for the task of bankruptcy prediction through time.

One more point that is worth considering refers to the prior research made in the field of bankruptcy prediction in Italy. There is a limited literature that is designed specifically for companies operating in Italy and even more limited research with respect to privately-held companies operating in Italy. One of the research projects was conducted by Pozzoli and Paolone (2016) and concerned with the validation of effectiveness of Altman Z'-score for unlisted companies that went bankrupt in the first quarter of 2016. The research has come up with the average predictive accuracy of 78.62% in the five-year period prior to bankruptcy. Another research was introduced by Gordini (2014) and employed artificial neural networks machine learning techniques to predict bankruptcy among Italian SMEs that went bankrupt in 2012. The research employed eight ratios of liquidity, profitability and leverage introduced in earlier literature that occurred to be significant and was able to make predictions with accuracy rate of non-defaulting firms equal to 64.2% and defaulting firms equal to 78.8%.

Overall, despite the fact that there are several papers that are designed to predict bankruptcy in Italy, the considered period is far from nowadays and the classification accuracy of the models is rather low. As was mentioned earlier by Grice and Ingram (2001), the structure of the models changes over time, as well as the importance of certain ratios, which requires constant update of models.

Summing up the results, recent research in the field of bankruptcy mostly relies on one of the following approaches in bankruptcy prediction modeling, which include the re-estimation and comparison of well-established models and development of new models. The new models are built with the employment of a considerable number of ratios and then tested for significance. It has been demonstrated that researchers tend to come to accurate results when they employ the combination of well-established models. Moreover, the scope reviews have demonstrated that ratios used in the models of Altman (1983) and Ohlson (1980) have been employed in the majority of research in combination with other variables. Hence, the model that will combine the financial indicators used in Ohlson (1980), Altman (1983) and Zmijewski (1984) research could be able to produce higher predictive accuracy than individual ones, as it happens in other research. As a result, the research will make an attempt to combine the existing widely-used financial ratios to test whether the new combined model will perform better than well-established models separately.

Overall, the significance of accounting-based models cannot be underestimated. Some researchers made a comparison of accounting- and market-based models on the example of publicly listed companies. Agarwal and Taffler (2008) compared the performance of KMV-option-based models (also referred to as market-based models) against Altman's Z-score model (accounting-based model). Results have shown that Z-score models slightly outperforms the market-based model, however, the difference between the two models is not statistically significant. However, Hillegeist et al. (2004), on the example of 78100 observations applied Black–Scholes–Merton Probability of Bankruptcy model (also referred to as BSM-prob) and compared the results with O-score (Ohlson, 1980) and traditional Z-score (Altman, 1968). Results have shown that BSM-prob significantly outperforms accounting-based models by 33% and 71% (Hillegeist et al., 2004). As a result, there is also no unique conclusion regarding whether the accounting-based approach is as good as market-based one or there is one prevailing approach.

Final remarks in this section should be made about the advantages and disadvantages that accounting-based models possess. Accounting-based models are criticized for being dependent on timing and sample; not taking account of market variables (Agarwal & Taffler, 2008). Hillegeist et al. (2004) argue that the use of accounting-based models to predict bankruptcy cannot be considered reliable since financial statements primarily exist in order to reflect the information of past time. At the same time, both going concern and conservatism principles hinder the achievement of reliable conclusions in terms of bankruptcy since the former assumes the long-term existence of the entity and latter can result in underestimation of assets. At the same time, accounting-based models have a considerable number of advantages. As demonstrated in the literature, models that employ accounting information are able to perform with accuracy exceeding 90%. Moreover, while accounting-based models employ information from financial statements that is publicly available and can be easily retrieved, market-based models usually lack some data like market value of assets or asset volatility which needs to be approximated which leads to large errors (Wu et al., 2010). In addition, Sloan (1996) emphasizes that market prices cannot accurately reflect the information from company accounts, which leads to the conclusion that accounting data should be used to complement market data. Despite all the disadvantages of the accounting-based models, advantages are still significant and justify the usage of accounting indicators to predict bankruptcy. Since for private companies it is impossible to derive company's market-based data, the use of financial indicators derived from financial statements is reasonable and justified.

Coming up to conclusion in this section, it is worth mentioning a few points. First, the models for bankruptcy prediction employing accounting indicators have been popular since the 1930's and remain one of the most reliable ways to predict bankruptcy. Second, despite the fact that the number of established models is incredibly high, the models Altman, Ohlson (1980) and Zmijewski (1984) remain the most-widely used and able to bring satisfactory classification accuracy. However, the classification accuracy varies depending on the country and research industry of interest. Third, in recent periods researchers tend either to combine the well-established models or develop models from scratch, testing groups of financial variables for significance. In the latter case most of the models employ at least several indicators that are used in the models of Altman (1983), Ohlson (1980) and Zmijewski (1984). In all cases, the resulting models tend to classify bankrupt and non-bankrupt firms on the samples with high classification accuracy. Finally, the previous research in the field of Italian companies has demonstrated that the attention to bankruptcy prediction for this country is very low and existing research was not able to produce high classification accuracy.

1.4 Bankruptcy prediction: Tools

Besides description of widely-used accounting-based models and variables used to predict bankruptcy, it is also of great importance to analyze the tools which researchers apply to build the models. According to Alaka et al. (2018), the performance of bankruptcy prediction models largely depends on the tools used for creating them. Hence, the choice of the appropriate method for the modeling is likely to provide better classification results.

The tools employed in the field of bankruptcy prediction can be largely divided into two main groups: statistical and artificial intelligence (Alaka et al., 2018). Statistical tools refers to the multiple discriminant analysis (also referred to MDA) and logistic regression, while the artificial intelligence tools largely rely on artificial neural networks (also referred to ANN), support vector machines, case based reasoning, genetic algorithm, decision trees and rough sets.

The first bankruptcy prediction model that employed the analysis, different from the univariate one, refers to the Altman (1968) model. In the research, Altman relied on the multiple discriminant analysis to create and estimate the model. According to Altman (1968), "MDA is a statistical technique used to classify an observation into one of several a priori groupings dependent upon the observation´s individual characteristics". The dependent variable in this model can take only two values, so that all the companies are classified either as bankrupt or non-bankrupt. Multiple discriminant analysis functions are presented in the form of linear combinations of a set of independent variables. The output of the modeling is a list of discriminant coefficients, that are used to classify firms as bankrupt or non-bankrupt based on chosen threshold value (Alaka et al., 2018). The principal advantage of multiple discriminant analysis is that it makes it possible to analyze a set of ratios simultaneously instead of assessing one ratio at a time (Altman, 1968). It is worth mentioning that there is a list of assumptions multiple discriminant analysis relies on. First, a dependent variable must be dichotomous, meaning that it can take only one of two possible values. Second, independent variables are normally distributed. Third, there is an equality in variance-covariance matrices for both bankrupt and non-bankrupt groups. Fourth, prior probability of failure and the misclassification costs are known and specified. Finally, there should be no multicollinearity meaning that there should be no close linear relationship (Balcaen & Ooghe, 2006). The multiple discriminant analysis approach is criticized for the number of issues. First, it is criticized by researchers for the number of assumptions it relies on. Second, MDA function, despite providing at glance easily interpretable results, does not provide conclusions on the importance of coefficients used (Alaka et al., 2018). Third, it sometimes brings results that contradict the intuitive logic in terms of signs (Balcaen and Ooghe, 2006). Finally, according to Agarwal and Taffler (2008) the models that employ MDA as a modeling technique, can only include quantitative variables. Despite some critiques, the MDA approach is still a commonly-used one in the issues of bankruptcy prediction that was implemented in the research of Slefendorfas (2016), Pozzoli and Paolone (2016), Gu (2002) and Altman et al. (2017).

Artificial Intelligence (also referred to as AI) tools have a variety of approaches that could be used for bankruptcy prediction. Nowadays, AI tools are considered as one of the most popular ones in the field of bankruptcy prediction (Alaka et al., 2018). The most commonly-used tools for bankruptcy prediction include ANNs and SVM. ANNs work by constructing a mathematical model for a certain system with unclear relationship between the inputs and outputs (Kasgari et al., 2013). ANNs have an outstanding ability of learning quality with input and output data (Kasgari et al., 2013). However, for such tools as artificial neural networks to work with high performance, large samples must be used (Kumar and Ravi, 2007). SVM uses a linear model and creates a separating hyperplane with the help of non-linear mapping of inputs into a high-dimensional space (Kumar and Ravi, 2007). As concluded by Iturriaga and Sanz (2015), SVM and ANNs are generally considered to bring higher accuracy rates, as compared to other tools. However, the AI tools, in particular, ANNs and SVM have a number of drawbacks. First, some artificial intelligence tools including SVM and ANN are usually reported to have non-transparent nature, as these models are usually seen as those having "black-box" nature (Alaka et al., 2018). Second, AI tools suffer from the absence of bankruptcy theory (Kasgari et al., 2013) and the responses of the network of ANN to certain variations of the inputs seems illogical (Coats and Fant, 1993). Finally, the main criticism stems from the fact that the results produced by SVM and

ANNs can hardly be understood as well as coefficients' interpretation is very complex and sometimes contradicts common sense (Chung et al., 2008).

Finally, the statistical tool that also gained much attention refers to the logistic regressions. The introduction of logistic regression in the field of bankruptcy prediction is tightly connected to the paper of Ohlson (1980), since for the first time logit tool for bankruptcy modeling was used in this research. According to Jackson and Wood (2013), logistic regression can be defined as a conditional probability model that employs maximum log-likelihood estimation for the prediction of a company's bankruptcy. There are a lot of benefits that logistic regression possesses. First, the approach allows the use of both quantitative and qualitative variables for modeling, as compared to multiple discriminant analysis which is restricted by quantitative variables only (Alaka et al., 2018). Second, the coefficients of the logistic regression model represent the actual importance of variables, which makes the result transparent to analysts (Balcaen and Ooghe, 2006). Third, as mentioned by Ohlson (1980), logit analysis does not need to rely on assumptions of prior probabilities of bankruptcy and normality of distribution of predictors, as compared to multiple discriminant analysis. However, the drawback that is tied to the employment of logistic regression refers to high sensitivity to multicollinearity issues, which can lead to the unstable performance and decreased accuracy of results (Balcaen and Ooghe, 2006). Moreover, several researchers report the high sensitivity of logit regression to outliers (Tsai and Cheng, 2012). Despite drawbacks, the logistic regression has attracted much attention and has been actively used in the research. Based on the research of Shi and Li (2019), among 321 papers from 1968 to 2017 at least 123 used the logistic model to forecast bankruptcy. Among the papers of researches working in this field it is possible to highlight Dambolena and Shulman (1988) that achieved a prediction rate of 98%, Zhang et al. (1999) who used logit model to make forecasts in manufacturing industry, Abdullah et al. (2008) and Pramudita (2021).

Much research has already been conducted in the field of comparison of statistical and AI tools to identify the best tool for bankruptcy prediction. However, taking into account the disadvantages that each of the approaches possesses, it is still hard to choose the only one tool for bankruptcy prediction (Alaka et al., 2018). After careful consideration of all the benefits and drawbacks of various tools, this research has come up to conclusion that logistic regression will be used for bankruptcy prediction in Italy for private small and medium enterprises. For this research it is of great importance to be able to conclude which variables play the most important role for the bankruptcy prediction. Moreover, the use of logistic regression overweighs multiple discriminant analysis in terms of the assumptions, since real-world data rarely follows normal distribution and some assumptions are more likely to be violated. Finally, the main goal of the research refers to obtaining the most accurate model. Despite the fact that ANNs and SVM generally provide better accuracy rates, there is a decent number of papers that demonstrate that logistic regression performs almost equally well or even better than the former two. The research of Jardin et al.(2011) demonstrated that ANN tool performs only one percent better than logistic regression in terms of accuracy, while Tsai and Cheng (2012) achieved the same accuracy rate of 86% for both SVM and logistic regression and Du Jardin and Séverin (2012) have found out that ANN performed a bit poorer than logistic regression with overall accuracy rates of 81.3% and 81.6%, respectively. As a result, the use of logistic regression in the current research seems to be the most appropriate.

Overall, the current literature review has provided a deep dive into the issue of bankruptcy prediction. First, the research has examined how the notion of bankruptcy is defined in the literature and according to the law of Italy. Second, the literature has examined the most widely-used models employed for bankruptcy prediction and considered the financial indicators used in the recently-developed models. The literature review has not been able to come up with a conclusion on the unique bankruptcy prediction model, since the various sets of financial indicators and tools produce varying results depending on the industry, country and economic conditions. Third, the research conducted in the field of bankruptcy prediction for privately-held enterprises and Italian companies has proved to be very limited, which has determined the necessity to build the model that will suit for bankruptcy prediction for manufacturing privately-held SMEs operating in Italy in the current conditions. Fourth, the close examination of statistical and AI tools for bankruptcy prediction has led to the conclusion that there is no unique tool that would suit every case. However, based on the advantages and drawbacks of various tools, the research has come up with a decision to use logistic regression for modeling.

CHAPTER 2. METHODOLOGY

2.1 Statistical methodology

2.1.1 Logit specification

After careful literature review the three established bankruptcy prediction models of Altman (1983), Ohlson (1980) and Zmijewski (1984) have been chosen for testing on the sample of privately-held manufacturing SMEs operating in Italy. The fourth model is a combined model Q that is formulated as a combination of indicators identified in the three above-mentioned models. The selected models and new combined model Q are built with the help of logistic regression (also referred to as logit). This statistical technique was chosen as the most relevant one during the literature review. The basic form of logistic regression was built in accordance with research of Martin (1977), Hosmer and Lemeshow (2000), Chen (2011) and Staňková (2022).

The occurrence of event of bankruptcy is identified by the presence of binary variable denoted as Y, where $Y_j = 1$ is associated with bankrupt class and $Y_j = 0$ is associated with a non-bankrupt class.

The linear predictor is defined as $\eta(x) = \beta 0 + \beta^T x$, where $\beta 0$ and β^T are defined as coefficients of regression, x is defined as as independent variable and $\beta^T x$ is a dot product which represents the sum of products of all βx's.

The dependence of $E(Y)$ from the linear predictor is determined with the link function. The link function is represented by the logistic function that has the following form:

$\mathrm{Logit}(\pi) = \log(\frac{\pi}{1-\pi})$, where π is a probability of bankruptcy event $(Y = 1)$ (1)

Then, the probability of bankruptcy is expressed as follows:

$$P(Y = 1|x_1, x_2, \ldots, x_n) = \pi(x) = \frac{\exp^{(\eta(x))}}{1+\exp^{(\eta(x))}} = \frac{1}{1+\exp^{-(\eta(x))}} \quad (2)$$

The probability of non-bankruptcy, consequently, is expressed as follows:

$$P(Y = 0|x_1, x_2, \ldots, x_n) = 1 - \pi(x) = \frac{1}{1+\exp^{(\eta(x))}} \quad (3)$$

The coefficients of linear predictor are predicted with the employment of maximum likelihood estimation. The log likelihood is defined as follows:

$L(\beta) = \sum_{j=1}^{n}\{Y_j \ln[\pi(x_j)] + (1 - Y_j)\ln[1 - \pi(x_j)]\}$ (4), where n is the number of observations and $j = 1,2,\ldots,n$.

Based on the logic explained above, the four models of Altman (1983), Zmijewski (1984), Ohlson (1980) and combined model Q are built. The difference of these models is in the set of independent variables that serve as a linear predictor. At the same time, the dependent variable will remain the same for all four models.

2.1.2 Models specification

The model of Altman (1983) is presented as follows:

$$Z' = \beta_0 + \beta_1 WCTA + \beta_2 EBITTA + \beta_3 EQTL + \beta_4 STA \text{ (5)},$$

where WCTA = Working capital/Total assets. The financial indicator is considered as a liquidity ratio that estimates the ability of the company to pay for its debts and obligations. Working capital is calculated as current assets - current liabilities (Altman, 1968). Ratio measures the proportion of assets which can be converted to cash quickly to pay for liabilities related to total assets. The ratio is expected to decrease as the firm approaches bankruptcy, since current assets, which the company can use to pay for its obligations, tend to diminish and result in the inability of the firm to follow the terms of obligation agreements.

EBITTA = Earnings before interest and taxes/Total assets. EBITTA is considered a productivity ratio since it shows how much profit a firm can generate from its assets excluding the effects of tax and interest deductions. According to Altman (1968), when total liabilities are higher than fair value of assets that are defined by their earnings power, the company is considered to enter bankruptcy.

EQTL= Book value of equity/Book value of total liabilities. EQTL is a ratio that reflects the extent to which companies' equity can decline before liabilities outweigh its assets and the company becomes bankrupt. Since it is impossible to calculate market value of equity for the firm, book value of equity is taken from the balance sheet of the companies.

STA = Sales/Total assets. X5 shows how efficient the company is in generating revenue from its assets. This ratio is also called a sales turnover ratio. When the value of X5 is low, it is possible to conclude that assets are not managed efficiently, since the portion of sales from total assets is small, which means that potentially the company could have generated more sales from the existing assets. It is worth noting that the variable is reflecting the industry effects. However, since the focus of this research is on manufacturing industry only, the measure can be considered appropriate for the model.

It is worth noting that in the original model of Altman (1983) one more financial indicator of Retained Earnings to Total Assets is used. The limitation of this research is that it cannot use this ratio for bankruptcy prediction. Retained earnings are calculated as Beginning Retained Earnings + Net Income (Loss) - Dividends. All the data for the sample is collected from ORBIS database, which does not provide any information on retained earnings, as well as information on dividends and other equity accounts for privately-held companies. The use of Net Income instead of Retained Earnings cannot be considered relevant, since this measure does not provide the estimate for cumulative income for the lifetime of the firm. Hence, it was decided to eliminate this ratio from the model.The model of Ohlson (1980) is presented as follows:

$$O = \beta_0 + \beta_1 SIZE + \beta_2 TLTA + \beta_3 WCTA + \beta_4 CLCA + \beta_5 OENEG + \beta_6 NITA + $$
$$+\beta_7 FUTL + +\beta_8 INTWO + \beta_9 CHIN \text{ (6)},$$

where SIZE =log(Total Assets /GNP price-level index). SIZE is considered as a measure of size of the firm. As considered by Ohlson (1980), the higher the size of the firm, the less the likelihood that it will go bankrupt, so it is expected to see the negative sign of the coefficient.

TLTA = Total Liabilities / Total Assets. TLTA shows what portion of a company's assets is financed by the debt. It is expected to see the positive sign of this coefficient, since the bigger part of assets is financed by debt, the more the likelihood of the company to go bankrupt.

WCTA = Working Capital / Total Assets. WCTA reflects which part of total assets is liquid. Working capital is calculated as Current Assets - Current liabilities. The sign of the coefficient is expected to be negative. The bigger the liquid part of assets, the more chances that company will be able to pay for its obligations and the less likelihood to go bankrupt.

CLCA= Current Liabilities / Current Assets. X4 is a liquidity ratio that is also known as current ratio. It is a measure that shows whether the firm can cover its current liabilities that are due within one year with its current assets. The coefficient sign is expected to be positive meaning that the higher the ratio, the less chances the firm has to cover its current liabilities with its current assets, the more chances for the firm to become insolvent.

OENEG estimates whether Total Liabilities exceed Total Assets. It is a binary variable that takes the value of one if total liabilities exceed total assets and zero if otherwise.

NITA = Net Income / Total Assets. X6 is also called a return on assets (ROA) ratio. It shows how efficient assets are in generating profit. The coefficient is expected to be negative due to the fact that the higher the ratio, the more efficient are the money invested in assets, the less likely the company to enter a difficult situation or bankruptcy.

FUTL = Funds Provided by Operations / Total Liabilities. X7 shows whether the company is able to cover its obligations with operating income. This is also considered as leverage ratio. The sign is expected to be negative, since the bigger part of liabilities can be covered by operating income, the less chances that company will face financial distress.

INTWO is a binary variable that is equal to one if net income was negative for the last two years and zero, if otherwise. If the value is equal to one, the company is more prone to bankruptcy, while the value of zero shows that income is either zero or positive, which decreases the chances that company goes bankrupt.

CHIN = (Net Income(t) - Net income(t-1))/(lNet income(t)l + lNet income(t-1)l), where t is a definition of last available year and t-1 is a value for the previous year. X9 reflects the change in net income (Ohlson, 1980). The coefficient is expected to take a negative value because the higher the net income as compared to previous, the higher the ratio, the more positive is the tendency of the company to earn more as compared to previous year, the less chances to face bankruptcy.

The model of Zmijewski (1984) is presented as follows:

$$\mathrm{Zm} = \beta_0 + \beta_1 \mathrm{ROA} + \beta_2 \mathrm{FINL} + \beta_3 \mathrm{LIQ}\ (7)$$

where ROA = Net Income/Total Assets. ROA is considered as a productivity ratio that shows how much income is generated from the use of assets of the company. The sign of the coefficient is negative, since the more efficiently a company uses its assets to generate profit, the less the likelihood that it will face bankruptcy.

FINL = Total Debt/Total Assets. FINL is a measure of leverage which shows which part of assets is financed by debt. The bigger part of assets is financed by the loan, the riskier the company is, the more chances to go bankrupt. That is the reason why the sign of coefficient is positive.

LIQ = Current assets/Current liabilities. The ratio is also called a current ratio, which is used to estimate the liquidity of the company. Since current assets are opposed to current liabilities, the sign of the coefficient is supposed to be negative. However, as turned out during the research, LIQ had a negative sign only in 3 out of 7 years but it has never been statistically significant (Zmijewski, 1984). The new combined Q model is initially presented by the following equation:

$$\mathrm{Q} = \beta_0 + \beta_1 \mathrm{SIZE} + \beta_2 \mathrm{TLTA} + \beta_3 \mathrm{WCTA} + \beta_4 \mathrm{CLCA} + \beta_5 \mathrm{OENEG} + \beta_6 \mathrm{NITA} + \beta_7 \mathrm{FUTL} + \\ + \beta_8 \mathrm{INTWO} + \beta_9 \mathrm{CHIN} + \beta_{10} \mathrm{EBITTA} + \beta_{11} \mathrm{EQTL} + \beta_{12} \mathrm{STA}\ (8)$$

The equation combines all the financial indicators used in the models of Altman (1983), Ohlson (1980) and Zmijewski (1984) without duplications of variables. At the same time, since the new model is developed, it is necessary to ensure that no multicollinearity is in place and the combination of significant predictors is chosen. Before the model is developed, the correlation matrix is built due to the fact that the combination of independent variables used in the described above models is likely to result in high correlation of some of those variables. The high correlation is associated with multicollinearity that should be avoided when working with logistic regression.

For the purpose of removing insignificant variables and selecting the set of financial indicators that affect the probability of bankruptcy, logistic stepwise forward and backward regression is used. The new variables are added and then others are deleted based on the statistical significance until no more predictors are included in the model (Xu & Chang, 2008). When the set of statistically significant predictors is found, variance inflation factors (VIFs) are found for all the predictors. If VIFs are less than 10, it is considered that there is no multicollinearity problem, while the VIF higher than 10 is evidence to assume that there is a serious multicollinearity problem (Lu et al., 2015).

The established linear predictors will be used in combination with logit specification to produce the models of Altman (1983), Ohlson (1980), Zmijewski (1984) and combined Q model. After models are built, the prediction quality will be assessed and a decision will be made regarding the most suitable model for the research object.

2.1.3 Prediction quality assessment

After the results are obtained, the four models are tested for the quality of prediction. The quality of the bankruptcy prediction model in the research is defined by the accuracy of classification of companies as bankrupt and non-bankrupt. For this purpose, Receiver Operating Characteristic (also referred to as ROC) curve and Area Under Curve (also referred to as AUC) are constructed. The use of ROC curve and AUC can be traced back to the research of Staňková (2022), Singh and Mishra (2016). The ROC curve is constructed as a plot of true positive rate against the false positive rate at different cut-off values (Jones, 2017). The Area Under Curve is a single number that serves as a metric to assess the performance of the model (Staňková, 2022). If the AUC score is equal to 0.5, it is the evidence to assume that the model is random, while AUC equal to 1 ensures that the model is perfect for prediction (Stein, 2007). Hosmer et al. (2013) proposed the following classification for AUC values: if the AUC is equal to 0.5, the model is considered to be random; if the AUC values are in the range from 0.5 to 0.7, the model is suggested to have a poor performance; if the AUC values are in the range from 0.7 to 0.8, the discrimination is considered as exceptional; the AUC between 0.8 and 0.9 is the evidence of excellent discrimination; AUC from 0.9 to 1 tends to show an outstanding discrimination.

Confusion matrix is also employed for assessing the quality of the bankruptcy prediction model. The choice of employment of confusion matrix is done based on the research of Staňková (2022), Affes and Kaffel (2019), Tseng and Hu (2010) and Kasgari et al. (2012). The confusion matrix is a classification metric that identifies the number of correctly predicted and incorrectly predicted observations. The matrix has four dimensions that are True Positive and True Negative observations that were identified by the model correctly and False Positive and False Negative observations that were identified by the model incorrectly. The incorrect classification is tightly connected to Type I and Type II errors. The Type I error refers to misclassification that occurs when an actual bankrupt firm is predicted to be a non-bankrupt one, while the Type II error refers to misclassification that occurs when an actual non-bankrupt firm is classified as a bankrupt firm (Altman, 1968). Both types of errors contribute to the deterioration of the model accuracy. However, the cost of Type I error is generally perceived as higher than Type II error, since the prediction of actually bankrupt firms as healthy is more costly than identification of healthy firms as bankrupt (Kingyens et al., 2016). Finally, the ratios of sensitivity and specificity are considered. Sensitivity refers to the percentage of bankrupt firms correctly classified, while specificity is associated with the percentage of non-bankrupt firms correctly classified (Veganzones & Séverin, 2018). The general representation of confusion matrix is presented in Table 2.

Table 2. Confusion Matrix

Actual / Predicted	Active	Bankrupt	Total
Active	True Negative	False Positive	Total predicted Active
Bankrupt	False Negative	True Positive	Total predicted Bankrupt
Total	Total actual active	Total actual bankrupt	Total number of companies

In the confusion matrix the positive class is associated with bankrupt firms, while the negative class refers to non-bankrupt companies. The ratios that are derived from confusion matrix and used to measure the quality of the model are as follows:

$$\text{Total Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \quad (9)$$

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive + False Negative}} \ (10)$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative + False Positive}} \ (11)$$

$$\text{Type I error} = \frac{\text{False Positive}}{\text{True Positive + False Negative}} \ (12)$$

$$\text{Type II error} = \frac{\text{False Negative}}{\text{True Negative + False Positive}} \ (13)$$

The optimal cut-off values are used to dichotomise the dependent variable as bankrupt or non-bankrupt (Unal, 2017). When identifying the cut-off value, it is widely spread to use 0.5 as a cut-off threshold (Staňková, 2022). However, for imbalanced samples the cut-off value of 0.5 is not an appropriate measure since it does not allow to appropriately predict less frequent cases that refer to the event of bankruptcy (Cramer, 1999). This research relies on the Youden index to identify the cut-off value, which is done in the similar manner to Staňková (2022), Savona and Vezzoli (2012). The Youden Index is used to find the optimal cut-off value (Fluss et al., 2004). The optimal cut-off value is obtained via the maximization of Youden function (Fluss et al., 2004) in the following manner:

$$\mathrm{J(c)} = \max_c\{\text{Sensitivity(c)} + \text{Specificity(c)} - 1\} \ (14),$$

where $\mathrm{J(c)}$ is the index of the Youden function and c is defined as a threshold value. For a maximum value of J, the corresponding threshold value c^* is considered as an optimal cut-off value. After results are obtained, the conclusion will be made regarding the most appropriate model for bankruptcy prediction for privately-held manufacturing SMEs operating in Italy.

2.2 Sample collection

The research requires a set of financial data in order to build Altman (1983), Zmijewski (1984), Ohlson (1980) and combined Q models. The financial data is considered as secondary data and is collected from the ORBIS database provided by Bureau van Dijk (Bureau van Dijk, n.d.). ORBIS database possesses comparable information on more than 450 million firms and is considered one of the most suitable resources for the search of data for privately-held firms.

The first criteria that was put for the sample collection refers to the country. The choice was restricted by Italy, meaning that only countries that were operating on the territory of Italy were considered. Second, the sample was narrowed down due to the status of the companies. As a result, the sample only includes bankrupt companies that are presented with status “Bankrupt” in the ORBIS database. The choice is consistent with the notion of bankruptcy employed in current research. Sample also includes non-bankrupt companies that are presented with status “Active” in the ORBIS database, which represent the companies that were operating in Italy in the observed period. The choice was made in a similar manner to the research of Sponerová (2022). Third, the limitation has been put to the period for which the sample of non-bankrupt firms was collected. For this research the period was chosen from 2018 to 2022 to be able to capture current conditions in which companies operate.

Among the set of remaining companies, only small and medium enterprises were chosen. European Commission recommendation 2003/361 considers small and medium enterprises (also referred to as SMEs) as companies with a number of employees smaller than 250, sales turnover between 2 and 50 million EUR or the total value of assets between 2 and 43 million EUR (Official Journal of the European Union, 2003). The criteria for the number of employees was set according to the definition that is less than 250 and companies with turnover/total value of assets more than 50 million EUR/43 million EUR respectively and turnover/total value of assets less than 2 million EUR were deleted. Since the research is focused on private firms solely, the standardized legal form was chosen as a private limited company, which is consistent with a description provided by ORBIS database (Bureau van Dijk, n.d.). Finally, to identify that company belongs to the manufacturing industry, NACE revision 2 codes were used. NACE industry classification defines the companies operating in similar industries in the European Union (Eurostat, n.d.). For the purpose of research, all the companies from the manufacturing block C representing manufacturing companies were chosen.

After data was collected, the observations with missing values were deleted. On this step, the sample consisted of 17 680 non-bankrupt firms and 884 bankrupt firms. Before the data is employed in the model, it is necessary to clear the data from outliers and consider the issue of balancing in the sample (Min & Jeong 2013). Before it is done, the financial ratios that serve as independent variables are constructed for each model.

Considering outliers, it is necessary to refer to the notion of outliers. There is still no unique definition of what can be considered an outlier, since it depends on the threshold for what constitutes an outlier (Tsai & Cheng, 2012). However, outlier detection is one of the most important tasks when working with data, since filtering data from outliers helps to increase the predictive accuracy of models (Tsai & Cheng, 2012). There are two widely researched ways of how bias which stem from outliers can be reduced refers to omission. These are winsorization and omission (Nyitrai & Miklós, 2019). Considering the fact that the sample of bankrupt companies is quite small, omission of outliers will result in further decrease in the number of bankrupt observations which is a highly undesired event, the current research will rely on the winsorization approach. All the non-binary variables have been winsorized on the 1st and 99th percentile in similar manner to Altman (2014) and Tian and Guo (2015).

After winsorization is done, it is necessary to make a note on the balancing issue. The sample is highly imbalanced, which is a common practice for such research. There are researches that employ paired samples with an equal number of bankrupt and non-bankrupt companies, which has an advantage of minimizing classification error (Zhou, 2013). However, such an approach significantly overestimates the occurrence of bankruptcy in the real world, where the ratio of bankrupt firms to non-bankrupt ones tends to be between one to one hundred and one to one thousand (Zhou, 2013). Hence, the study will not rely on pairing mechanisms. On the current step the proportion of bankrupt to non-bankrupt firms is approximately one bankrupt firm per twenty non-bankrupt firms, which is also not a clear representation of a real-world situation, however, is consistent with proportions identified by Ohlson (1980). According to Nyitrai & Miklós (2019), the presence of imbalance can affect the model performance, however, it is not a serious problem for linear classifiers.

Final point that should be considered is division of the sample on training and testing ones. The training sample will consist of 90% of all the observations, while the rest 10% will fall on the testing sample keeping the proportion of the sample. The percentage choice is consistent with choice in research of Gilenko et al. (2013), Fedorova et al. (2013). Overall, the sample consists of 18570 observations, where 17691 represent non-bankrupt firms and 879 represent bankrupt firms. The balance is approximately one bankrupt firm per twenty non-bankrupt firms, which means that no additional balancing procedure is done. The training sample consists of 791 bankrupt and 15922 non-bankrupt firms, while the testing sample has 88 bankrupt and 1769 non-bankrupt firms. Table 3 demonstrates how data is distributed among samples.

Table 3. Sample Size

Step	**After the step**		
	Non-bankrupt	**Bankrupt**	**Total**
Collecting initial data	17 691	879	18 570
Selecting the training sample	15 922	791	16 720

Selecting the testing sample	1 764	93	1 857

2.3 Sample description

The section covers the descriptive statistics on the variables that are employed in the research for modeling and bankruptcy prediction. Table 4 demonstrates descriptive statistics for the established sample:

Table 4. Descriptive statistics for variables

Variable	Bankruptcy	Minimum	Median	Mean	Maximum	Standard deviation	T-stat
Altman (1983)							
WCTA	Non-bankrupt	-0.231	0.278	0.280	0.762	0.209	15.1***
	Bankrupt	-9.677	-0.100	-0.534	0.754	1.517	
EBITTA	Non-bankrupt	-0.135	0.048	0.068	0.357	0.078	12.8***
	Bankrupt	-5.288	-0.021	-0.324	0.410	0.862	
EQTL	Non-bankrupt	-0.023	0.463	0.774	5.128	0.905	35.74***
	Bankrupt	-0.918	0.005	-0.036	3.307	0.607	
STA	Non-bankrupt	0.302	0.979	1.045	2.643	0.440	2.47**
	Bankrupt	0.001	0.736	0.957	6.180	1.000	
Zmijewski (1984)							
ROA	Non-bankrupt	-0.131	0.032	0.047	0.268	0.061	12.5***
	Bankrupt	-5.560	-0.027	-0.351	0.349	0.891	
FINL	Non-bankrupt	0.163	0.683	0.657	1.024	0.209	-15.5***
	Bankrupt	0.232	0.995	1.634	12.210	1.764	
LIQ	Non-bankrupt	0.628	1.645	1.961	7.356	1.128	22.1***
	Bankrupt	0.024	0.870	1.076	7.647	1.102	
Ohlson (1980)							
SIZE	Non-bankrupt	9.524	10.798	10.794	12.017	0.544	44.08***

	Bankrupt	6.010	8.793	8.918	11.514	1.191	
TLTA	Non-bankrupt	0.163	0.683	0.657	1.024	0.209	-15.5***
	Bankrupt	0.232	0.995	1.634	12.210	1.764	
WCTA	Non-bankrupt	-0.231	0.277	0.280	0.762	0.209	15.1***
	Bankrupt	-9.677	-0.100	-0.534	0.754	1.517	
CLCA	Non-bankrupt	0.136	0.608	0.637	1.592	0.276	-10.7***
	Bankrupt	0.131	1.150	2.525	41.193	4.934	
OENEG	Non-bankrupt	0.000	0.000	0.013	1.000	0.109	-26.8***
	Bankrupt	0.000	0.000	0.491	1.000	0.500	
NITA	Non-bankrupt	-0.131	0.032	0.047	0.268	0.061	12.5***
	Bankrupt	-5.560	-0.027	-0.351	0.349	0.891	
FUTL	Non-bankrupt	-0.175	0.071	0.142	1.116	0.205	23.5***
	Bankrupt	-0.888	-0.016	-0.089	0.911	0.273	
INTWO	Non-bankrupt	0.000	0.000	0.050	1.000	0.217	-18.6***
	Bankrupt	0.000	0.000	0.372	1.000	0.484	
CHIN	Non-bankrupt	-2.587	0.181	0.409	9.101	1.379	14.14***
	Bankrupt	-5.627	-0.243	-0.228	4.138	1.223	
* significat at 5% level ** significant at 1% level *** significant at 0,01% level							

The research uses T-test for equality of two means in order to identify the variables that differ significantly for bankrupt and non-bankrupt groups in terms of mean values. The choice of the test is consistent with research of Singh and Mishra (2016), Jackson and Wood (2013). Results demonstrate that the null hypothesis of mean equalities is rejected for all the variables in all three models, hence, it can be concluded that means differ significantly among bankrupt and non-bankrupt companies. Hence, the bankrupt companies tend to have financial indicators that are significantly different from non-bankrupt companies.

Considering the Altman (1983) model, it can be noted that for bankrupt companies all the financial indicators have a mean value that is lower than for non-bankrupt firms. It is anticipated that this outcome would occur, since the approaching of company to bankruptcy is tightly connected to the decrease in working capital that can be used to pay for liabilities, the weaker ability of the firm to generate profit from its assets, higher level of indebtedness characterized by Equity to Total Liabilities ratio and decreased ability to generate profit. Minimum values for all financial indicators are all smaller for bankrupt firms, than for non-bankrupt ones. However, maximum values for bankrupt firms in cases of EBITTA and STA exceed the maximum values for non-bankrupt firms. The reason for this could be connected with the fact that bankruptcy is a long-term process (Bal, 2016). Companies can slowly but steadily head to bankruptcy, while generating profit. This profit, on the other hand, is not sufficient to cover all the liabilities. Another reason could be that despite assets being productive and able to generate sales, it is still not enough to cover all the liabilities of the company. Summing it up with standard deviation that is generally higher for bankrupt firms and reflects the spread of values from the mean, the situation differs from company to company, reflecting that while some ratios can be higher for one bankrupt firm, other indicators are likely to suffer. This result is consistent with conclusions of Altman (1968) with respect to the employment of univariate analysis of ratios, where the whole picture cannot be captured, when financial ratios are analyzed one at a time.

As for the Zmijewski (1984) model, mean values are much higher for ROA and LIQ among non-bankrupt firms, while the mean of FINL is higher for bankrupt companies. The outcome is also consistent with expectations. While non-bankrupt firms tend to demonstrate higher rates of liquidity and potential to generate income from the use of assets, bankrupt firms are more prone to finance their operations with borrowed funds.

The descriptive financial indicators of Ohlson (1980) model is also in line with what was expected. Larger firms are less likely to face bankruptcy, as compared to small ones. Moreover, non-bankrupt companies tend to have higher levels of working capital, reflect higher levels of liquidity and have higher capabilities in terms of financing its obligations with operating income. Finally, the CHIN ratio clearly demonstrates the tendency of non-bankrupt firms to earn more net income, in line with the diminishing ability to do so among bankrupt-companies which generate less and less income when approaching bankruptcy. Bankrupt firms, on the other hand, are characterized by the prevalence of current liabilities and total liabilities exceeding total assets, which is clearly demonstrated by means for TLTA and CLCA that are higher for bankrupt firms.

CHAPTER 3. RESULTS AND MANAGERIAL IMPLICATIONS

3.1 Results

The three models of Altman (1983), Zmijewski (1984) and Ohlson (1980) are built with the use of logistic regression and the training sample of 15 929 non-bankrupt and 791 bankrupt firms. Before the prediction accuracy is considered, it is worth looking at the descriptive statistics of the models.

In the model of Altman (1983) all coefficients turn out to be significant on the 5% level. Moreover, the signs of coefficients turn out to be negative either, which is consistent with Altman et al. (2014). Such a result implies that higher amounts of working capital as compared to total assets, higher productivity of assets resulting in higher profits as compared to total assets, higher reliance on equity instead of debt and higher sales as compared to total assets decrease the probability of the company to enter bankruptcy, while the decrease in these ratios increases the probability of the company to enter bankruptcy.

As for the Zmijewski model (1984), all the coefficients also demonstrate the significance on the 5% level. Considering signs of the coefficients, ROA has a negative sign, meaning that increase in productivity of assets of the company decreases the chances of the company to go bankrupt, as well as decrease in the ratio makes the company closer to bankruptcy. At the same time, FINL and LIQ demonstrate the positive signs. FINL shows the level of indebtedness of organization and the higher reliance on debt in the company imposes higher risks in terms of bankruptcy. Current ratio is expected to have a negative sign; however, the results demonstrate a reverse trend, which is counter-intuitive in nature, however, similar to results obtained by Zmijewski (1984).

Considering Ohlson (1980) model, all coefficients except for OENEG turned out to be significant. OENEG is a binary variable that demonstrates whether the total liabilities exceed total assets. As follows from the results, this is an insignificant predictor of firms' bankruptcy. The higher the prevalence of total liabilities over total assets and current liabilities over current assets, the higher the likelihood of a company entering bankruptcy. Size has a negative sign, which is logical due to the fact that the higher the size of the firm, the less chances it has to file for bankruptcy (Ohlson, 1980). Same applies for CHIN, where the negative change in net income contributes to the higher likelihood of the event of bankruptcy. At the same time, FUTL and WCTA are expected to have negative signs, however, the situation is different. The difference in coefficients and their signs is a common situation, since the differences have been identified in the research of Singh and Mishra (2016) and Grice and Dugan (2003) when re-estimating the Ohlson model. The models' summary is presented in Table 5.

Table 5. Models' coefficients

Variable	Estimate	P-value
Altman (1983)		
Intercept	-1.3319***	0.000
WCTA	-2.5160***	0.000
EBITTA	-6.9379***	0.000
EQTL	-1.7942***	0.000
STA	-0.7888***	8.11e-14
Zmijewski (1984)		
Intercept	-9.6219***	0.000
ROA	-7.1661***	0.000
FINL	7.5259***	0.000
LIQ	0.1912**	0.00947
Ohlson (1980)		
Intercept	-0.21552***	0.000
SIZE	-2.93985***	0.000
TLTA	3.69940***	1.92e-14
WCTA	3.05740***	4.84e-05
CLCA	3.28086***	9.78e-13
OENEG	0.06618	0.803627
NITA	-11.03405***	4.55e-11

FUTL	4.44529***	3.40e-11
INTWO	0.76286***	0.000517
CHIN	-0.18714**	0.003502
* significant at 5% level ** significant at 1% level *** significant at 0,01% level		

Considering the combined model Q, it is presented initially by the following equation:

$$Q = \beta_0 + \beta_1 \mathrm{SIZE} + \beta_2 \mathrm{TLTA} + \beta_3 \mathrm{WCTA} + \beta_4 \mathrm{CLCA} + \beta_5 \mathrm{OENEG} + \beta_6 \mathrm{NITA} + \beta_7 \mathrm{FUTL} + \\ + \beta_8 \mathrm{INTWO} + \beta_9 \mathrm{CHIN} + \beta_{10} \mathrm{EBITTA} + \beta_{11} \mathrm{EQTL} + \beta_{12} \mathrm{STA} \quad (15),$$

where TLTA, FUTL, EQTL represent solvency ratios, WCTA, CLCA represent the liquidity ratios, NITA and EBITTA are profitability ratios, STA is efficiency ratio, CHIN represents the change in net income, INTWO and OENEG represent binary variables.

Since some of the ratios tend to have a common denominator and close sense, the issue of strong correlation could occur, hence, the correlation matrix is built for the variables that are used to build the combined Q model. The correlation matrix is presented in the Appendix 1. As expected, there are correlations between some variables; that is, between working capital to total assets (WCTA) and total liabilities to total assets (TLTA), between net income to total assets (NITA) and earnings before interest and tax to total assets (EBITTA), between net income to total assets (NITA) and total liabilities to total assets (TLTA). The high correlations are associated with an issue of multicollinearity. First, the stepwise regression approach is employed to build the model. After the procedure is finished, the summary is obtained for combined model Q. The summary is shown in Table 6:

Table 6. Combined model Q coefficients and VIFs

Variable	Estimate	P-value	VIF
Intercept	43.4466***	0.000	
WCTA	2.4634**	0.00907	8.866
EQTL	0.5534*	0.0283	7.749
STA	-3.4485***	0.000	1.821

SIZE	-4.9095***	0.000	1.838
TLTA	5.1005***	6.70e-09	5.660
CLCA	2.9848***	4.10e-07	8.028
NITA	-11.7135**	4.97e-08	5.284
FUTL	5.0245***	1.89e-08	7.874
CHIN	-0.2768**	0.00103	1.159
* significant at 5% level ** significant at 1% level *** significant at 0,01% level			

As can be noted from Table 6, all variables are statistically significant and the variables OENEG, INTWO, EBITTA have been excluded from the model. The correlated variables NITA and TLTA and WCTA and TLTA have not been excluded, hence, the model should be tested for the issue of multicollinearity which is always a serious problem for logistic regressions (Tucker, 1996). The VIF test is conducted for the variables in order to detect if there is an issue of multicollinearity. VIFs are presented in Table 6. As can be derived from the results, there are no VIFs higher than 10, hence, no multicollinearity issue is detected. The model Q will be taken for testing predictive accuracy. Hence, the final outlook of the model Q is as follows:

$$\mathrm{Q} = \beta_0 + \beta_1\mathrm{SIZE} + \beta_2\mathrm{TLTA} + \beta_3\mathrm{WCTA} + \beta_4\mathrm{CLCA} + \beta_5\mathrm{NITA} + \beta_7\mathrm{FUTL} + \\ + \beta_8\mathrm{CHIN} + \beta_9\mathrm{EQTL} + \beta_{10}\mathrm{STA} \ (16),$$

Overall, the models of Altman (1983), Ohlson (1980), Zmijewski (1984) and combined Q model have the form demonstrated in Table 7:

Table 7. Equations of models

Model	**Equation**
Altman (1983)	$Z' = -1.3319 - 2.5160 * \mathrm{WCTA} - 6.9379 * \mathrm{EBITTA} + -1.7942 * \mathrm{EQTL} - 0.7888 * \mathrm{STA}$
Ohlson (1980)	$O = -0.2155 - 2.9398 * \mathrm{SIZE} + 3.6994 * \mathrm{TLTA} + 3.0574 * \mathrm{WCTA} + +3.2808 * \mathrm{CLCA} + 0.0662 * \mathrm{OENEG} - 11.0340 * \mathrm{NITA} + + 4.4452 + \mathrm{FUTL} * 0.7628 * \mathrm{INTWO} - 0.1871 * \mathrm{CHIN}$

Zmijewski (1984)	$\mathrm{Zm} = -9.6219 - 7.1661 * \mathrm{ROA} + 7.5259 * \mathrm{FINL} + 0.1912 * \mathrm{LIQ}$
Combined-Q model	$\mathrm{Q} = 43.4466 - 4.9095 * \mathrm{SIZE} + 5.1005 * \mathrm{TLTA} + 2.4634 * \mathrm{WCTA} + +2.9848 * \mathrm{CLCA} - 11.7135 * \mathrm{NITA} + 5.0245 * \mathrm{FUTL} - -0.2768 * \mathrm{CHIN} + 0.5534 * \mathrm{EQTL} - 3.4485 * \mathrm{STA}$

After models are constructed, their predictive ability is tested. As stems from the methodology, two approaches are used to test the performance of the model. First, the Receiver Operating Curve is constructed for each of the models and AUCs are obtained. Both ROC and AUC are obtained for test samples. The AUCs are presented in Table 8:

Table 8. Models' AUC

Model	**AUC**
Altman (1983)	0.874
Ohlson (1980)	0.963
Zmijewski (1984)	0.897
Combined Q-model	0.968

As can be seen from Table 8, all of the models were able to demonstrate rather high AUCs, however, the Ohlson (1980) and combined Q models demonstrate the highest AUC, meaning that these two models provide the highest ability to differentiate between bankrupt and non-bankrupt companies, with combined model Q having slightly higher AUC and being a very strong classifier. According to Hosmer et al. (2013) classification, the models of Altman (1983) and Zmijewski (1984) tend to demonstrate an excellent discrimination, while the models of Ohlson (1980) and combined Q show an outstanding discrimination.

It is also worth considering the performance of models in terms of the number of firms correctly and incorrectly classified. For this purpose, confusion matrix is employed. The optimal cut-off point has been obtained with the help of maximization of the Youden index; its values are demonstrated in the Appendix 2. The results are presented in Table 9.

Table 9. Confusion matrices

Altman (1983)		
Actual / Predicted	**Active**	**Bankrupt**
Active	1685	27
Bankrupt	84	61
Zmijewski (1984)		
Actual / Predicted	**Active**	**Bankrupt**
Active	1655	22
Bankrupt	114	66
Ohlson (1980)		
Actual / Predicted	**Active**	**Bankrupt**
Active	1739	7
Bankrupt	30	81
Combined Q model		
Actual / Predicted	**Active**	**Bankrupt**
Active	1738	5
Bankrupt	31	83

Table 9 demonstrates that the model of Ohlson (1980) demonstrates the highest ability to identify non-bankrupt firms, while the combined Q model does the best job in terms of correctly identifying bankrupt firms.

Then, the ratios of the predictive quality of the models are considered. The description can be found in Table 10.

Table 10. Predictive quality of models

	Overall performance	**Sensitivity**	**Specificity**	**Type I error**	**Type II error**
Altman (1983)	94.02%	69.32%	95,2%	30,68%	4.8%
Ohlson (1980)	98.01%	92.05%	**98.34%**	7.95%	**1.66%**
Zmijewski (1984)	92.68%	75.00%	93.56%	25%	6.44%
Q-model	**98.06%**	**94.31%**	98.25%	**5.69%**	1.75%

The model of Zmijewski (1984) has the lowest overall accuracy of 92,68%. At the same time, it demonstrates satisfactory measure of specificity and second lowest percentage of sensitivity. Sensitivity is expected to be lower, since the sample is highly imbalanced, however, sensitivity demonstrates the percentage of correctly classified bankrupt firms, which is more important when identifying bankrupt firms, as compared to non-bankrupt ones. The model of Altman (1983) demonstrates a bit higher accuracy rate of 94,02%, however, was able to capture only 69,32% of bankrupt observations. The model of Ohlson performed with the second highest accuracy in terms of overall performance and was able to capture 98,34% of non-bankrupt firms and 92,05% of bankrupt firms. Finally, the combined Q-model has the highest overall accuracy rate of 97,85%, was able to capture 94,31% of all bankrupt firms, representing the highest sensitivity among all the examined models. As for the Type I and Type II errors, it is possible to highlight that misclassification rates of both non-bankrupt firms classified as bankrupt firms and bankrupt firms as non-bankrupt ones are the lowest for combined Q model and Ohlson model. Type I error is lowest for combined Q model, while Type II error is lowest for the Ohlson model. In the case of bankruptcy prediction, the cost of Type I error is higher, since the risks that company or any other stakeholder bears when recognizing a bankrupt firm as non-bankrupt is higher when non-bankruptcy firms fall into the bankrupt category. Overall, the study shows that the implementation of Q model for the context of bankruptcy prediction for privately-held small and medium manufacturing companies operating in Italy is the most appropriate, since the combined Q model was able to differentiate between bankrupt and non-bankrupt firms in the given setup most accurately.

The study contributes to the existing literature in several ways. First, it tests the applicability of well-established models on the sample of privately-held manufacturing small and medium companies operating in Italy. Second, it introduces the enhanced combined Q-model that combines ratios used in the proved models. Third, the study finds out that the new combined Q-model is the most suitable model among those chosen for analysis and comparison that can be used in the researched context and can make predictions one year prior to the event of bankruptcy with an overall accuracy rate of 98,06%.

The research provides a bunch of advantages that stem from the development of the Q-model that should be highlighted. First, the established model is available to everyone. Unlike the models used by the banks that are not freely available to everyone or giant corporations developing their own default costly models, this model is very narrowly targeted and is able to bring very high results in terms of prediction of bankruptcy without additional costs. Anyone can reintroduce the model with the use of various tools, including RStudio and Python. Second, the model is able to bring a prediction rate equal to 98,06%, which is very high for the context of bankruptcy of companies operating in Italy. Considering the highly imbalanced sample, which is closer to the real-world situation, as compared to models tested on the samples where the number of bankrupt and non-bankrupt firms is equal, the model was still able to bring satisfactory results. When comparing the results to those produced by Pozzoli and Paolone (2016) and Gordini (2014) that were introduced in the literature review, it is pivotal to highlight that the combined model Q significantly outperformed the tested models of the researchers in terms of the classification accuracy.

3.2 Limitations

Although the study has a considerable contribution into the field of research in the area, it has certain limitations. The study is limited by the defined research object, that is, privately-held small and medium manufacturing companies operating in Italy. Results cannot be extrapolated to the other industries and countries without testing due to several reasons. First, the model itself employs the ratio of Sales/Total Assets, which is a highly industry sensitive ratio, hence, its value can vary from one industry to another, creating evaluation mistakes in case multiple industries are used (Altman, 1983). Second, the limitation occurs due to the differences in reporting standards. Italian small and medium limited companies are obliged to present the balance sheet and profit and loss statements in accordance with Organismo Italiano di Contabilità (OIC) standards (LLoyds Bank, 2023). At the same time, the standards according to which financial statements are made differ from country to country. The differences occur even between Organismo Italiano di Contabilità OIC standards and IFRS standards. For example, while the IFRS standards are based on fair value and are investor-oriented, the OIC standards are based on historical value and are creditor-oriented (Baldissera, 2019). Finally, the need to test the model stems from the prior research made in the field of bankruptcy prediction, where different researchers come to different results when applying the same model to different countries and economic conditions. Hence, prior to using the model for bankruptcy prediction outside the research frame, the model must be tested, since the changing conditions are likely to violate the quality of performance.

3.3 Managerial Implications

The advantages of the research create opportunities for different groups of stakeholders. Hence, there are several managerial implications that are addressed in the following paragraphs.

First, the model is useful for the management of the company. While large corporations are more likely to afford installing a special software that will automatically organize and analyze the data about financial health of the company, small and medium enterprises are those companies that in some cases cannot yet afford buying such licenses. At the same time, SMEs are more prone to the financial instabilities and their financial health should be checked regularly. Combined model Q is a simple tool to address this need. By inserting the relevant data into the model, it can immediately provide the result which will indicate if the company is experiencing difficulties. If so, the management of the company can on its own try to understand what is going wrong in the company or attract external workforce to deal with impending problems. No matter what choice is made by the company, the model can help management realize that there are certain challenges that are now being experienced by the enterprise and make an action before it is too late to rectify the situation.

Second, the model is beneficial to investors and potential investors of the company. When a company is not a large organization but on the stage of development, it definitely needs funds to evolve. It is much harder for small and medium enterprises to attract funding from banks; hence, another choice is concerned with appealing to investors. Investors are those stakeholders for whom it is a must to check the financial health of the company they are investing in or planning to invest in. All the investors want to have returns on the invested money and no one is willing to lose their funds. As a result, they should regularly analyse the financial state of the company. For them, the model can be handy in two ways: either as an express tool to check that no serious problems are faced by the organisation or as a diversification of existing methods that helps to summarise the one-by-one ratio analysis. In the first case, all the data can be inserted in the model and a single number result is appeared, so it is useful to do a verification regularly, as soon as new data is provided. In the second case, the model result acts like a summary. Investor makes a fundamental analysis of all ratios and then checks whether the company is approaching bankruptcy with the help of the model. Sometimes it can be hard to interpret the result of a fundamental analysis, since some of the variables can talk in favour of financial health of the company, while others are signalling about certain challenges. The model helps to capture the values of all ratios and combine them to produce a definite result that is easier for investor to perceive.

Finally, the model can even serve as a helpful tool for buyers and suppliers of the company. Companies the model is made for are ones that are operating in the manufacturing industry. To let the manufacturing process begin, such companies usually apply to external suppliers to acquire some resources, for example, raw materials of spare parts. At the same time, manufacturing companies can produce either the ready-to-use products or the goods that act like a basis for further production. In both cases the buyers of the company can be either individuals or other companies. While for the individual buyers who go to the shop and buy the product the model is not of a great interest, for companies that use goods of the manufacturing company as inputs model will be a crucial tool. When looking at the process from the side of supplier of manufacturing company, it is clear that intentions of the supplier are in maintaining stable sale of goods with no interruptions so that the planning process runs smoothly and in gaining constant profits that are used to manage their own business. When entering relationships with a small or medium company, the supplier beforehand puts himself into the higher risk of failure of relationships when compared to the large companies. Hence, supplier company has to analyze the financial health of the buyer and make sure that the company will not be left without money for provided goods. The model can again act as a quick check of the health of the company or a tool that helps summarizing the analysis. From the side of the buyers, buyer company is also interested in the stability of its operations, since it is dependent on the resources that manufacturing company is providing to it. When establishing long-term relationships, it is also necessary to analyze the position of the company and make sure there are no serious risks that potentially can heart the operating cycle.

Overall, the benefits provided by the developing and testing of combined model Q on the sample of privately-held manufacturing SMEs operating in Italy can be easily utilized by the companies falling into this category. More importantly, the model will also suit the stakeholders of such companies that can save their funds and/or operations and ensure their stability when using the model.

CONCLUSION

Bankruptcy is a widely-known problem that can potentially touch on every organization. Bankruptcy is not just an issue that can easily be resolved. Bankruptcy is a final stage of existence of an enterprise, which has consequences for people and companies somehow connected with it.

The problem existed a long time ago and its relevance is only increasing with the growth of the number of enterprises. Every company is in need of a special framework or tool that could be deployed easily to predict bankruptcy as early as possible. Such tools could be used to realize that something goes wrong with a company's management. When management is aware of serious problems, the company is given a chance to survive and eliminate the vulnerabilities. The work on the bankruptcy prediction tools started in the 1930s and is still continuing. Great progress has already been achieved, however, one of the conclusions of the whole work refers to the need to validate existing models and/or develop new models for each and every economic, business condition and country.

The thesis has addressed the issue of bankruptcy for the special case of privately-held small and medium manufacturing enterprises operating in Italy. Such a narrow object was chosen due to the research gap associated with such a group of enterprises, which are undoubtedly crucial and central to the economy of Italy. To achieve the research goal the academic literature has been considered including the notion of bankruptcy according to the Italian law and works of various researchers, approaches to the prediction of bankruptcy, accounting-based models employed and results achieved among samples and statistical tools employed by researchers to build models.

The research compared the prediction quality of well-established models of Altman (1983), Ohlson (1980) and Zmijewski (1984) on the sample of privately-held manufacturing SMEs operating in Italy which was collected with ORBIS database. Then, the research combined the most recognized financial indicators to arrive at the combined model Q and compared the accuracy of the four models on the established sample. All the four models were built with the help of logistic regression as the statistical tool is considered as one of the most reliable ones and makes it possible to compare results produced by each of the models. Overall, the research goal has been achieved: the combined Q model was able to predict bankruptcy at the rate of 98.06% one year prior to bankruptcy. Hence, the research gap has been fulfilled because the solution for the niche of manufacturing companies operating in Italy has been found.

The research results create value for stakeholders in that it provides a simple tool for assessing the company that could be easily utilized by the company itself, investors, employees, buyers and suppliers without additional investments. The solution provides valuable insights regarding the state of the company nowadays and its possible development in the near future.

Those insights could be considered by the mentioned groups of stakeholders to make informed decisions when entering relationships with the companies operating in the researched field.

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APPENDIX

Appendix 1

Correlation Matrix

Table 11. Correlation Matrix

	SIZE	TLTA	WCTA	CLCA	OENEG	NITA	FUTL	INTWO	CHIN	EBITTA	EQTL	STA
SIZE	1	-0.45	0.35	-0.25	-0.39	0.33	0.15	-0.13	0.06	0.30	0.31	-0.50
TLTA		1	-0.88	0.60	0.51	**-0.71**	-0.42	0.28	0.00	-0.70	-0.51	0.19
WCTA			1	-0.68	-0.47	0.69	0.38	-0.26	0.02	0.68	0.37	-0.08
CLCA				1	0.37	-0.46	-0.22	0.22	-0.02	-0.45	-0.23	0.04
OENEG					1	-0.45	-0.27	0.39	-0.06	-0.45	-0.21	0.01
NITA						1	0.47	-0.27	0.09	0.99	0.22	-0.12
FUTL							1	-0.28	0.03	0.53	0.64	0.05
INTWO								1	-0.06	-0.28	-0.14	-0.09
CHIN									1	0.08	-0.05	-0.00
EBITTA										1	0.23	-0.08
EQTL											1	-0.226
STA												1

Appendix 2.

Maximised Youden Index

Table 12. Maximised Youden Index

Model	Index
Altman (1983)	0.101
Ohlson (1980)	0.133
Zmijewski (1984)	0.094
Combined Q	0.082