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Corporate Financial Distress and Bankruptcy Risk Prediction: An Empirical Analysis in the Italian Financial Sector

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INTRODUCTION

Investigating the causes of corporate financial distress and failure is still one of the most discussed financial topic since the 70s. Researchers continue to publish articles and works with the aim of discovering the nature of financial distress, considering different characteristics of the sector, the region or the type of corporation. The reason for the popularity is certainly to be found in the severity of the consequences of corporate bankruptcy. Indeed, a long-lasting situation of financial distress leads to corporate bankruptcy, that is, the death of a company.

The consequences of a business failure are hard to be addressed and they have strong impact not only on the company itself, but also on the employees, stakeholder, linked companies and on the global economic situation. As a matter of fact, direct and indirect costs of bankruptcy are particularly high and cannot be ignored. Big failures phenomenon in the 90s give rise to a vast literature of studies concerning corporate bankruptcy and, more interesting, the possibility to anticipate and predict those negative situations.

The vast majority of bankruptcy prediction studies focused on the importance of analyzing accrual accounting-based ratios. Thus, scholars developed their model using accounting information taken from the balance sheet and the income statement. Accounting information is certainly a key point to observe when detecting for financial instability. However, there are other variables that very often are not considered in the models and, if considered, will probably increase their failure predictive power. Such variables are the ones given by the cash flow statement.

Some few researchers stated that cash flow information provide a more reliable alert of failure than other accounting-based one, since data are not subjected to earning manipulations and accounting allocation by the management. Moreover, they believe that cash is an important indicator of financial conditions, since cash is what is used to buy things, pays wages and salaries, and pays debts (Bhandari et al., 2013).

The aim of this work is to contribute to the literature that support the predictive ability of cash flow data by developing a bankruptcy prediction model which include both accrual accounting-based ratios and cash flow ratios. In particular, my analysis will be specifically referred to the Italian Financial sector.

The paper is dived as follow: in the first chapter, I am going to review the literature in order to better understand the concept and the terminology of corporate financial distress, failure and bankruptcy. Then, the principal causes of failure are described with a particular attention to the peculiarity of business lifecycle and corporate governance, which influence the probability of bankruptcy. Furthermore, pages are dedicated to the importance of predicting corporate bankruptcy and its relative direct and indirect costs. Finally, the last part of the chapter, helps us to understand the context of the empirical analysis. As a matter of fact, is important to consider the regulatory framework: from a general overview of the EU directive, to the bankruptcy regime in Italy, and the relationship with the Italian Financial service industry.

The second chapter will be dedicated to the review of the bankruptcy prediction models. These models are generally divided in three macro categories: the accounting-based models, which take information from the company's financial statements; the market-based models, which use market data such as the share price, and the hybrid models, which combine both. Accounting based models remain the most popular and we can further divide this category in sub-categories namely, discriminant analysis models, regression models for definite variables, and survival analysis. From a general overview, I will go through the model that is more likely to be used in the empirical analysis. Therefore, among the discriminant analysis models, literature differentiates, considering the number of variables, the Univariate analysis from Multivariate analysis. Modern literature also introduced models based on artificial intelligence, which highly contributes to improve the accuracy of the forecasting but remain less practical than the traditional one. At the end of the second chapter, I will start to introduce my thought, by stressing the importance of cash flow information in bankruptcy prediction studies.

In the third chapter, I am going to build a new bankruptcy prediction model based on eight financial ratios: five from income statement and three from the operating cash flow. This model will be applied to a sample of Italian companies. The sample companies are publicly limited companies by share, not listed in any stock exchange, belonging to the financial sector. In this chapter, I am going to explain the starting point of my analysis, and the reason why I choose this specific sample of data. Then, I will go through the development of the analysis step by step and finally, I will discuss the result of the empirical test.

A final chapter is dedicated to the conclusion. After a recap of the conclusive remarks, I am going to present the limitations of the work that can be used as a starting point for related further researches, with my suggestions. Finally, I discussed about the potential theoretical and practical implications of my study for scholars, companies, and financial analysts.

CHAPTER I

Corporate Financial Distress

1.1 Introduction to Financial Distress

During the 1970s, the phenomenon of corporate failure gained some exposure, more during the recession years from 1980 to 1982, increased attention few years later with the wave of defaults and big company bankruptcies, and exceptional interest in the corporate collapse and distressed years of 2001–2002Consco's large filings ($56.6 billion in liabilities), WorldCom ($46.0 billion), and Enron ($31.2 billion — the biggest bankruptcy in the United States — capped the list of major corporate bankruptcies. Two of these three major bankruptcies were fraud-related (Altman & Hotchkiss, 2006). Moreover, in 2003, he Parmalat group's collapse has made corporate bankruptcy studies a major concern for scientists over the following years. In 2007, however, one of the worst worldwide crises hit the business environment; in September 2008, Lehman Brothers declared bankruptcy, a public bailout was rejected and hence collapsed. A credit crunch turned into a global financial crisis, it originated in the United States, then Europe became involved less than a year later. This global economic crisis is considered the worst since the Great Depression of the 1920s and 1930s (Paolone & Pozzoli, 2017). Therefore, despite the raised interest over this topic, the efforts to foresee these big failures have not been successful in the past years. This is the reason why, studies over bankruptcy prediction continued to increase steadily until now.

This first section of this chapter aims to define the concept of corporate financial distress, at first by reviewing the wide panorama of definitions present in the literature. Secondly, it's important to define the business lifecycle of an enterprise and the corresponding features related to each phase, in order to better understand where financial distress is located and, if the corrective measures differ according to the stage in which distress occurs. Then, the chapter continues with the analysis of the potential causes of distress and failure, separating internal causes, which depend on the firm's specific characteristics, from external causes, which rely on macroeconomic and environmental variables. Finally, it is worth giving special attention to the impact of corporate governance on business failure.

1.1.1 Literature review and terminology

Corporate distress, including corporate bankruptcy, restructuring (Chapter 11 of Bankruptcy code) and liquidation (Chapter 7) "is an economic reality that reflect the uniqueness of the American status of company death" (Altman & Hotchkiss 2010).

Financial distress reflects a negative status that is extended in time, during which a company experiences deteriorating financial conditions such as low liquidity, inability to pay debts, restrictions on dividend allocation policies, increased cost of capital, reduced access to external sources of funding, and weaker credit ratings (Agostini 2018).

Given the absence of a standard definition, many authors over the years, made the effort to define Financial Distress. As a matter of fact, a lack of a consistent definition of when companies enter that stage of decline was a roadblock that limited the attempt to predict financial distress (Platt and Platt 2002). In the early literature, Wruck (1990) states that a firm is in financial distress when it is unable to meet current cash obligations, interpreting financial distress as cash flow *insolvency*. This definition of failure matching with the concept of insolvency was approved by many other scholars (Walter 1957; Altman and Hotchkiss 2010; Beaver 1966).

Lau (1987) and Hill et al. (1996) use layoffs, restructurings, or missed dividend payment to classify corporations that might be considered in distress. However, it has been proven that these variables are sometimes existing in companies even if they are not actually in financial suffering (Platt and Platt 2002). These difficulties in finding a definition are probably the reason of the scarce success in prior empirical efforts regarding financial distress. Moreover, Whitaker (1999) measures distress as the first year in which cash flow is less than current maturities of long-term debt; and John, Lang, and Netter (1992) define distress with the fluctuations in the equity price.

The variety of definitions include also the one of Purnanandam (2008) who interpreted financial distress as an intermediate state between solvent and insolvent, underlining the difference between financial distress and insolvency. As a matter of fact, a firm can be in low cash-flow state (distress) and experience losses, without being insolvent.

From another point of view, authors examined the connection between financial distress and profitability. DeAngelo and DeAngelo (1990) identified financially distressed companies as those that have three consecutive years of negative net income. Differently, Asquith, Gertner, and Scharfstein (1991) allowed the interest coverage ratio to define distress, and few years later Andrade and Kaplan (1998), considered the ability of the earnings before interest and taxes, depreciation and amortization (EBITDA) to cover financial expenses.

Others more recent scholars, Pindado, Rodrigues, and de la Torre (2008) continued to use this technical methodology based on the relationship between the operating profitability and the financial obligations, to determine whether a firm is in financial distress. In particular, they believe that a corporation requires two conditions: EBITDA lower than its financial expenses for two consecutive years, and a fall in its market value for two consecutive periods. This latter technical definition relies on the analysis of the financial ratios from the company's financial statement, considering the idea that they can represent good predictors of failure (Paolone & Pozzoli 2017).

In addition to these definitions, Platt and Platt (2006) consider financial distress as a broader concept meaning a negative lasting status that generally precedes the *bankruptcy*.

Bankruptcy constitutes an everyday example of a legal event that marks the end of a company's life cycle. Indeed, if a corporation cannot or fails to take remedial actions to deal with the causes of financial distress, the consequences are the forced bankrupt and asset liquidation.

For this reason, financial distress is often associated with the likelihood of bankruptcy, despite they represent two different situations and surprisingly, most distressed firms do not become bankrupt (Hill, Perry & Andes 2011). Indeed, while bankruptcy represent a single event, financial distress is more a path and a dynamic process, made by a sequence of steps (Agostini 2018).

To better understand the vague term of financial distress, Altman (2006) strived to highlight the distinction among four generic terms that financial distress encompasses: failure, insolvency, default, and bankruptcy. These four terms sometimes are used interchangeable, but they have different formal usage.

Failure is more an economic term, this implies that the realized rate of return on invested capital, with allowances for risk consideration, is considerably and continuously lower than prevailing rates on comparable investments. *Insolvency,* exists when a firm is not able to cover its current liabilities, meaning a lack of liquidity. When this status is persistent, is called "chronic insolvency" and can easily lead to bankruptcy. Another corporate condition that is associated with distress is *default*. Defaults can be technical and/or legal. Technical default takes place when the debtor violates a condition of an agreement with a creditor and can be the grounds for legal action, in this latter case, it become a legal default. Finally, *Bankruptcy* refers to a formal announcement by the court. The firm declared bankrupted is asked to liquidate its assets (Chapter 7) or to implement a recovery plan (Chapter 11) in the US context.

Some academics do not consider bankruptcy as the best legal alternative of emergency and that in many instances the mandatory ceasing of operations interrupt businesses, that could give back more resources to the community (Ball and Foster 1982). Based on this idea, the reorganization theory of Chapter 11 allows failing corporation to continue to run under the debtor's management and controller, with the aim of preventing the death of corporations, whose intrinsic or economic value is greater than their current liquidation value. By contrary, if the firm's asset values are worth more dead than alive, liquidation is the preferable option (Altman and Hotchkiss 2006).

1.1.2 Business life cycle theory

Financial distress, default and bankruptcy are fundamental stages in the lifecycle of firms (Wruck, 1990). The business life cycle generally consists of four stages: birth, growth, maturity and decline.

According to the *life cycle theory*, growing capacity, access to resources, and strategies vary during a firm's life cycle (Anthony and Ramesh 1992). Each stage presents significant differences in terms of situation, organizational strategy, structure, and decision-making style. In particular, distinct lifecycle characteristics influence mainly the restructuring decisions

In the earlier stages of their life, firms are typically small, simple and informal in structure, with a centralized power and focus on innovation (Adizes 2004; Miller and Friesen 1984; Pashley and Philippatos 1990). Logically, the level of uncertainty over the future growth is high and this is reflected in higher book-to-market ratio and firm specific risk (Pastor and Veronesi 2003). Corporate financial distress in the birth stage is generally associated to weak liquidity level or parallel cash flow difficulty (Hasan et al. 2015). In the following stage, firms may achieve rapid growth, in this case, corporate financial distress is usually connected to excessive financial leverage because of the apparent necessity to expand capital (Agostini 2018). Differently, in the maturity stage firms are usually less focused on innovation and on risky strategy than in the previous stages. Indeed, they are interested in stabilizing their business in the market.

Finally, the life cycle includes a phase of *decline*, when the company operates under financial distress and its performance worsens for consecutive periods. If the causes are not corrected the decline become crisis and then failures.

According to this theory, corrective measures and restructuring strategies adopted by firms facing corporate financial distress can also be of different types and may be affected by the physiognomies of the lifecycle (Koh et al. 2015). Indeed, some recovery strategies are adopted by each firm, as reducing investment or reducing dividends, but some others are strictly related to the stage in which the distressed company found itself. For instance, a common restructuring strategy in the earlier stages is to reduce the number of employees, while in the maturity stage, generally the strategies involve asset rearrangement.

Sudarsanam and Lai (2001) provide four classifications of restructuring: managerial, operational, asset, and financial: *Managerial restructuring* includes replacement of senior management and/or the Chief Executive Officer and it does not directly encompass cash. *Operational restructuring* decisions aimed to control the costs and improve the efficiency by selling fixed assets, reducing investments, spending (Capital, R&D), and costs (COGS) minimizing the input and maximizing the output (Koh et al. 2015) (Lasfer & Remer 2010). Differently, *asset restructuring* implies the reduced unrelated diversification and a greater focus on the core competencies (Shleifer and Vishny 1992) by selling off assets through divestments, spin-offs, and equity carve-outs, merging with another company, and acquiring assets. It typically generates much needed cash quickly, but it is considered to be an extreme option (Robbins and Pearce 1993). Finally, when a firm need to change the dividend's policies or the capital structure, we refer to *financial restructuring* including those strategy such as issuing new securities, switching debt for equity and cutting or neglecting dividends (Koh et al. 2015). In the birth stage of a firm, the authority is concentrated and is more probable that the managers are also the owner, thus, it is clear that a managerial restructuring will not occur. However, when the firm grows, its structure become more complex and managers become more likely to be replaced for their poor performance.

1.1.3 Causes of Failure

As previously mentioned, insolvency or the inability to pay debt, has been the main concern in most of the primary bankruptcy literature (Piesse, Lee, Kuo and Lin 2006).

Some of the most shared causes of insolvency are suggested by Rees (1990):

- Low and declining real profitability;
- Unfitting diversification: moving into unfamiliar businesses or failing to move away from deteriorating ones;
- Import penetration into the firm's domestic markets
- Worsening financial structures
- Complications controlling new or geographically isolated processes
- Over-trading in relation to the investment base
- Insufficient financial control over contracts
- Scarce control over working capital
- Failure to remove actual or potential unprofitable activities
- Adverse changes in contractual arrangements.

However, this classification regards only the definition of corporate failure as synonymous of insolvency, and it does not consider any nonfinancial causes.

We can organize the determinants of corporate financial distress dividing internal causes from external or micro-level and macro-level variables.

- Micro-level determinants and internal causes:

On the micro level, company's specific characteristics must be considered, such as the company's size, maturity, industry and flexibility. Altman (1971) found that the age of the firm significantly impacts the possibility of bankruptcy. If we take in consideration the business life cycle mentioned in the previous paragraph, companies are more likely to fail in the first stage and in the decline state, while in the medium ones (growth and maturity) the likelihood of bankruptcy is limited. Indeed, a new and small company is generally perceived riskier than a mature one and the probability of failing is higher during the first three years of its life.

A study conducted by Thornhill and Amit (2003) provides evidences to this theory, showing that young firms are riskier, and they are more likely to go bankrupt due to deficiencies in managerial knowledge and financial management abilities, while older firms may have problem to adapt to changes in the environment. Young firms may lack capital to cover financial obligations due to the high initial investments and resources required, or they lack industry-related experiences and capabilities to establish a competitive position. External factors may not have a great influence on these companies. Differently, growing companies are generally vulnerable to bankruptcy due to a lack of flexibility in reacting and adapting to changes in the environment. Finally, for older and well-established firms, failures can arise from changes in the competitive landscape together with a lack of commitment and motivation or from an exaggerated risk taken strategy (Ooghe and De Prijcker, 2008).

Interestingly, Corporate Social Responsibility affect the likelihood of bankruptcy. Al-Hadiet al. (2017) with his study conducted in Australia, find that companies with good CSR performance are less inclined to experience financial distress and that this association is more visible for firms in the mature stage of their life cycle. Certainly, since mature firms have greater resources and easy access to finance, they have more probability to involve in positive CSR compared to young firms (Hasan and Habib, 2017). The negative relationship between CSR performance and distress risk has been proven also by Chang et al. (2013) in Taiwan and by Shahab, Ntim & Ullah (2019) for Chinese firms.

Additional factors that conditionate the proxies of financial distress are the R&D investment levels. According to Zhang (2015), R&D investments are connected with high uncertain payoff, which increase the likelihood of bankruptcy. Also, this relation become stronger during downturn economic period and for controlled firms. Moreover, Kane et al. (2005) find that firms with good employee relations experience lower distress risk and it contributes to the solidity of the company's value.

In general, bankruptcy risk is higher when uncertainty over the future firm's value increase. For this reason, activities such as corporate hedging strategies reduce the risk, since hedging aims to minimize the volatility of the firm's value over time (Stulz 1996).

Argenti (1976) summarized previous related studies identifying the internal causes of failure to be:

1. Bad management showed through
   (a) absence of responsiveness to change in technology
   (b) bad communications
   (c) misfeasance and fraud
   (d) inadequate consideration for cost factors (research and development costs in particular)
   (e) poor knowledge of financial materials
   (f) high leverage position-particularly destructive in an economic downturn

Finally, from an accounting perspective, Bodle et al. (2016), find that by using IFRS standards instead of the Australian GAAP, the superiority of information increase and thus the ability of predicting bankruptcy. This is true especially for the accounting treatment of intangible assets.

- Macroeconomic and external causes:

  Despite the majority of the studies relate corporate bankruptcy to managerial errors (Ooghe and De Prijcker, 2008; Altman & Hotchkiss 2010), which depends on manager's qualities, skills, motivation and personal characteristics, there might be many external causes coming from both the general and the immediate environment that affect the corporate's policy and performance.

  Some of these non-managerial reasons include the nature of the industry (Chronically sick businesses as agriculture and textile), deregulation of some key industries (Airlines, energy, financial services) which increase the quantity of entering and leaving firms in the market landscape, high real interest rates in certain periods, international competition, overcapacity within an industry and high likelihood for new business development (Altman & Hotchkiss 2010).

  Altman (1971) was one of the first researcher who analyzed the influence of macroeconomic variables on corporate failure. He found that the probability of default increases with a tight monetary policy, when investor's expectations about economic conditions are negative and finally, when the state of the economy worsens.
  According to Chordia and Shivakumar (2005), Bonsall et al. (2013), macroeconomic variables account for approximately half of the difference in firms' earnings and earnings deviations. The economic condition of a country impacts upon the business environment through fluctuations in inflation rates, interest rates, employment rates, credit accessibility and monetary policy (Liou and Smith, 2007). As a matter of fact, the predictive power of bankruptcy prediction models can increase by incorporating country risk features (Tinoco and Wilson, 2013; Altman et al., 2017).

  Argenti (1976) synthetize the main external factors leading to distress in three categories:

1. Labor Unions: Too high a wage settlement imposing the firm to pay its employees in excess of their marginal product.
2. Government Regulations which impede, in some occasions, the working of the market system twisting in the process its indicators to the company decision makers.
3. Natural causes: Natural catastrophes, demographic changes, etc.

However, although the most common causes of bankruptcy can be noted, they are not sufficient to explain or predict corporate failure. A company with any one or more of these characteristics is not certain to fail in a given period of time (Piesse, Lee, Kuo and Lin 2006).

1.1.4 Corporate Governance and Financial Distress

A considerable body of modern literature has been focused on the impact of corporate governance over future financial distress conditions.

The general definition of corporate governance includes a set of mechanisms, processes and relations by which corporations are measured and directed (Shailer, 2004). An integrated set of internal and external control mechanisms will allow shareholders to exercise proper omission of a company to maximize firm value and ensure that it generates a return on their holdings (Chen, 2014).

Corporate governance can explain financial crisis better than macroeconomic variables (Johnson et al. 2000). A study conducted by Lian, Lu, Tsai and Shin (2016), explored the opportunity to improve the power of bankruptcy prediction models by combining the main financial ratios (profitability, solvency, cash flow ratios, capital structure ratios, growth, turnover and other) with corporate governance indicators (Board structure, ownership structure, cash flow rights, retention of key personnel and others). The result of the study, based in Taiwan, shows that financial ratios categories of profitability and solvency, together with the governance indicators of board structure and ownership structure are the most important features in bankruptcy prediction. The principal features of corporate governance are better analyzed in the following lines.

Board structure: conclusions over the board structure are quite inconsistent among various researchers. Some authors conclude that there is a positive correlation between board size and the possibility of bankruptcy, while some other did not find any similar features (Habib, D'Costa, Huang, Bhuiyan and Sun, 2018). For some of them (Jensen, 1993; Lipton & Lorsch, 1992; Darrat, Gray, Park and Wu, 2016; Fich & Slezak, 2008; Yermack, 1996) small size boards are more efficient in monitoring due to better coordination and less free ridings. While for some others, (Dalton and Daily, 1999; Coles et al. 2008; Boone et al. 2007; Linck et al. 2008) large and diversified boards generally deliver better guidance to the CEO.

An interesting result concern the separation of the roles of the chairman and the chief executive office. As a matter of fact, firms with CEO duality (accumulation of powers of two figures in a single person) have high likelihood of financial distress.

Regarding the independence of the board, literature generally focuses on the monitoring role of the board and reports that more independent board are associated with more efficient monitoring, which reduces the agency problem (Darrat, Gray, Park & Wu, 2014). Thus, firms with high proportion of independent directors have less likelihood of financial distress (Manzaneque, Priego and Merino, 2015).

Finally, personal characteristics of the CEO, such as gender, level of confidence, managerial ability and social ties, may affect the possibility of failure. For example, female presence in the board generally is associated with higher risk aversion (Habib, D'Costa, Huang, Bhuiyan and Sun, 2018).

Ownership structure: whether a more concentrated ownership is exposed to higher risk of bankruptcy is not a common result from literature (Habib, D'Costa, Huang, Bhuiyan and Sun, 2018). The debate over the hypothesis is still in place. Nevertheless, Gottardo and Moisello (2017) found that family firms are less likely to incur in bankruptcy compared to non-family firms. Generally, family ownership firms are interested also in non-economic goals, such as the emotional attachment or the willingness to keep the business alive for the future generations Anderson and Reeb, 2003; Berrone et al., 2012). As a result, the strategy will be focus on the long-term survival rather than on risky and short-term one (Habib, D'Costa, Huang, Bhuiyan and Sun, 2018).

1.2 Bankruptcy Prediction

The deeply understanding of the term "financial distress" allows us to identify failure, default and bankruptcy. However, the paper focuses its attention on the ability to predict these corporate failures. The following section will better explain why it is important to predict bankruptcy and which have been the incentives for the development of the related research. Finally, this section includes the analysis of the costs associated with bankruptcy, differentiating the direct costs of bankruptcy from the indirect ones, also by taking into consideration the differences in the main bankruptcy procedures of liquidation and reorganization.

1.2.1 Reasons for predicting Bankruptcy

Corporate failure and bankruptcy have been two interested topics of research for more than 35 year, especially, the effort in trying to avoid and predict those negative conditions has been great. Considerable academic studies were made in order to deliver accurate models of corporate failure prediction. The reasons are many and because of their severity they cannot be ignored (Balcaen and Ooghe 2004).

First, there are many stakeholders including economic agents, financial institutions, auditors, consultants, policy makers and clients that are directly affected by the failure of a firm. Some of them probably have direct claims on the firm, while some others hold contracts whose value is tied to the distressed firm (Ayotte & Skeel, 2010). Therefore, studies regarding financial distress prediction were stimulate by both private agents, who aim to take corrective and preventive measure to address failure causes, and by the government, who concern about avoiding the failure of some corporations. Governments and central banks in particular, developed models for assessing financial health of firms and encouraged firm to adopt preventive policy against financial difficulties and provide problematic firms with advisory services in order to reduce the probability of failure.

Secondly, researches were stimulated by the negative spiral of the economy (Tamari, 1966; Van Caillie & Dighaye, 2002). Over the past 30 years, the economic condition for some countries changed rapidly and the firm performance worsen due to the tougher competitive environment in which firms operate. The increased competition arises from the globalization during the new era, which also lead to an increased regulation (Balcaen and Ooghe 2004). In many countries, given the increased vulnerability of companies, bankruptcy rates have risen and therefore, the need for predicting models increased.

Thirdly, great progresses in quantitative techniques contribute to the developing of bankruptcy prediction models based on mathematics and statistics but also information and artificial intelligence applications (Van Caillie & Dighaye, 2002). Furthermore, researchers were able to access large financial information of the companies since most of them become listed, and thus allowing them to analyze the data in a more precise way (Van Caillie & Dighaye, 2002).

Fourthly, failure prediction studies were boosted by the impact of market imperfection and information asymmetry on credit ratings (Balcaen and Ooghe 2004). In contradiction with Modigliani & Miller (1958), who assume that financial markets are perfect, and that investment and financing decisions can be separated, it has become clear that financial markets are not perfect. Indeed, the funds available are not enough to implement every project that entail a positive net present value. This means that a selection process is essential and must include a risk assessment of the projects and the companies (Balcaen and Ooghe 2004).

Finally, failure prediction models that allow to identify failing firms, are proven to be essential in order to correctly evaluate a firm’s financial situation more than independent assessments by auditors (Altman & McGough, 1974).

1.2.2 Costs associated with Bankruptcy

According to Branch (2002) the bankruptcy process imposes costs on a very wide array of parties including the owners and direct creditors of the troubled firm and many other parties. For example, those having contacts with (landlords, suppliers, customers, employees, etc.) or potential claims against (e.g., product liability claims) need to be considered when the magnitudes of bankruptcy costs are assessed. Moreover, since a significant part of the value of the bankrupt firm is consumed in dealing with its distress, bankruptcy costs play an important role in determining the optimal capital structure.

Modigliani and Miller (1958) did not consider bankruptcy costs in their model because they assume that markets are perfect, and investors behave rationally. Therefore, in a tax-less world, the capital structure is irrelevant to the value of the firm (Haugen and Senbet,1978) and no debt/equity ratio could be regarded as optimal (Warner, 1976). According to the MM theory, there is no necessary linkage between bankruptcy and the firm's operating performance. Hence, bankruptcy has no economic consequences.

Some years later, Kraus and Litzenberger (1973), Scott (1976) and Kim (1976), have formally introduced bankruptcy costs in their models. By considering a corporate tax in which interest payment can be deducted from the net income, they relax the assumption that bankruptcy is costless, and they reopen the possibility for an optimal debt/equity ratio.

As mentioned in the first paragraph, when the firm experiences a decline which end with the legal event of bankruptcy, there are two different procedures that can be taken: Liquidation and Reorganization. These two procedures correspond to the decision of whether to fil under chapter 7 (liquidation) or under chapter 11 (reorganization) of the US bankruptcy code.

When facing this decision, it is important to consider the costs associated with the respective procedure.

Liquidation. Liquidation is a capital budgeting decision that occurs when the market value of the dismantled assets exceeds their aggregate value as the organized, ongoing firm. Which means that, the total value of the assets when dismantled and sold piecemeal, less any associated costs, is greater than the total market value of the assets of the firm as given by the price that clears, a competitive market (Haugen and Senbet, 1978).

When firm files for liquidation (Chapter 7), it is asked to liquidate its assets. The proceeds from the sale are then distributed to creditors according to the absolute priority rule (APR). Under the APR, administrative expenses related to the bankruptcy procedure are paid first, secondly taxes, rent and wages, thirdly unsecured creditors (trade creditors, bondholders and often banks) are paid in full, and lastly, the remainder goes to equity (White, 1982).

This process of failing firms displaces managers and equity become worthless. Consequentially, managers and equity holders generally have a strong incentive to avoid liquidation, both because they lose their jobs and/or their shares and because the firm also loses its net operating loss carryover (often its most valuable asset) (White, 1982). Thus, they will try to postpone the liquidation and make the bankruptcy time longer.

Reorganization. When the firm's value is greater than the reorganization cost, the firm is likely to file under chapter 11 and obtain the confirmation for a plan of reorganization. The aim of the process is primarily a rehabilitation of the distressed firm (Senbet and Seward, 1995), providing debtor with the legal protection and creditors with going- concern value rather than a 21eager satisfaction of outstanding debt through liquidation (McCormack, 2017). Usually, large firms with huge debt and complex structure are worth to be saved. Which means that the benefits from saving the company are greater than the benefits from selling its assets. Among the failure of large American corporations, most of the largest corporate bankruptcy file under chapter 11, Conseco, WorldCom, and in 2008 the experience of Lehman Brothers expressing the idea of "too big to fail". Specifically, the number of unemployed people reached to 590000 in the United States in January 2009, setting a record high in the last 17 years. In this case, investigating the bankruptcy probability and avoiding the failure of such big entities becomes crucial for authors, market participants and regulators.

On average, bankruptcy costs ranged from 11% to 17% of firm value up to three years prior to bankruptcy (Altman, 1984). The failure of some big economic entities produces high costs for the society. For this reason, law and procedures have been established in order to protect the contractual rights of interested parties, to provide for the orderly liquidation of unproductive assets and to provide the opportunity to reestablish the current financial distress and to emerge from the process as a continuing entity (Altman & Hotchkiss, 2010).

When bankruptcy occurs, there is a transfer of ownership and a reorganization of the firm capital structure. The costs associated with this transfer can be categorized as either direct or indirect.

Direct costs are those explicit and administrative costs paid by the debtor in the reorganization/liquidation process. Direct costs include legal, accounting and trustee fees as well as the possible denial' of income tax loss carryovers and carrybacks. The direct cost of dealing with bankruptcy is largely in the form of fees paid to professionals, especially lawyers and accountants (Branch, 2002).

Indirect costs relate to the opportunity costs resulting from disruptions in firm-supplier or firm-customer relationships that are associated with the transfer of ownership or control (Haugen & Senbet, 1978). Indirect costs of bankruptcy include lost sales, lost profits, the higher cost of credit, or possibly the inability of the enterprise to obtain credit or issue securities to finance new opportunities (Altman, 1984). Within the indirect costs are also inter or intra group conflict of interests, asymmetric information and free rider problems.

Indirect bankruptcy costs are not limited to firms which actually do fail. As a matter of fact, these types of costs can occur either before and after the company is declared failed. For instance, firm may lose sales and profit when potential buyers perceive that default is likely. Moreover, suppliers of materials may be reluctant to continue to sell to high risk players, or they might compensate the risk asking for higher costs. Differently, indirect costs arising after the formal declaration of bankruptcy, are related to the effort of recovering.

Indirect costs are generally perceived as substantially larger than the direct ones (Senbet and Seward, 1995). Nevertheless, direct cost of bankruptcy can be easily measured because some quantitative information is available, while indirect costs are mainly "lost of opportunities" or "expected losses" and consequently, they are difficult to measure (Warner, 1976). However, *time* in bankruptcy could be a proxy for measuring indirect cost of bankruptcy (Franks and Torous, 1989; Thorburn, 2000). Indeed, it has been proven that indirect bankruptcy costs such as bankruptcy's adverse impact on product and capital markets increase with the time that firms spend in bankruptcy (Bris, Welch and Zhu, 2006).

1.3 Institutional Context and Regulatory Framework

When dealing with bankruptcy, it is necessary to consider the institutional context and the regulatory framework. The bankruptcy regulation defines the criteria for which an enterprise can be declared insolvent and then bankrupted. Moreover, the law clarifies the bankruptcy procedures of liquidation and reorganization. Since this paper is based on an empirical study over a sample of Italian companies from the financial sector, the following section will give at first, an overview of the European directive and some comparison with the U.S. bankruptcy code, later, the Italian regulation will be discussed more specifically. Finally, an overview of the financial sector and the related financial crisis is presented to explain the choice of the sector.

1.3.1 The European Directive

Since 1960, the evolution of the European Insolvency Regulation (EIR) has taken about 40 years (Paulus, 2008). When cross-border company transactions increased, the need for a comprehensive and harmonized corporate bankruptcy law emerged, and firms became increasingly international with both their physical presence and market operations. (Virgòs and Garcimartìn, 2004). Multinational trade entails the risk of cross-border insolvency. As a matter of fact, when assets are located across different countries, one single insolvency can involve creditors and properties located in many countries, each of which has different insolvency laws (Burton, 1999). Many countries at the European level recognized the importance of the harmonization of insolvency laws for creation of internal market (Akšamović, 2018).

The Insolvency regulation aims to provide a set of uniform rules to be applicable to each Member state and to establish an area of freedom, security and justice. In particular, the insolvency regulation seeks to achieve 3 goals: provide legal certainty in cross-border insolvency; promote the efficiency of insolvency proceedings, by providing solutions that facilitate the administration and improve ex-ante planning of transaction; to eliminate inequalities among creditors with regards to these proceedings.

However, as previously stated, each state has different insolvency laws which reflect different political goals and social ambitions that need to be respected. For instance, France puts a lot of emphasis on protecting the rights of the labor workforce and preserving jobs while the Germans give the balance of power to creditors so they can maximize their recovery (Burton, 1999).

In general, some countries are more creditor-friendly (usually common law countries), while some other are more debtor-friendly (civil law countries) (Detotto, Serra e Vannini, 2019). These differences in goals may create problems in taking a collective decision regarding the proper bankruptcy proceeding.

Bankruptcy law in European countries, for some aspects significantly differs from the one in the Unites States. Nevertheless, the proceedings are the same of liquidation and reorganization.

For these three European countries, French, Germany and United Kingdom, a collective bankruptcy *liquidation* is similar to that in the United States but is less likely to be used.

The French liquidation procedure is the most similar to that in the US. However, the main difference is that, the distressed firm is subjected to a period of observation of minimum six months from an outside court, which take the responsibility for the final decision (Bhandari, Adler and Weiss, 1996). Differently, in Germany and Britain, liquidation generally occurs outside bankruptcy and it is not a collective procedure (creditors do not seek satisfaction only through the insolvency proceedings, since individual actions are allowed (Welles, 2006)). In Germany there is no discharge of unpaid debts in bankruptcy, which means that you remain bankrupt for life unless you pay your debts in full (Boshkoff, 1994). In Britain, liquidation is managed privately by secured creditors rather than by an outside court.

As regards to the *reorganization* decision, Germany, as many other European countries, drew its insolvency plans following the model of Chapter 11 of the United State Bankruptcy code, with its concept of absolute priority. Nevertheless, reorganization in German is not common for many reasons, including the relatively minimum gain to creditors, the high required repayment rate to unsecured creditors and the high cost of a bankruptcy filing (Bhandari, Adler and Weiss, 1996). Conversely, France and Italy provided a debtor-protective proceeding by taking the liquidation route only after a failed reorganization attempt (Balz, 1996).

In order to provide an equal treatment of the creditors and coordinate national insolvency procedures, the European commission proposed many unsuccessful drafts for an insolvency convention (Balz, 1996; Akšamović, 2018). The process of harmonization went slowly over the years.

The first step forward was in 1995 when the Convention on Insolvency Proceeding was published by the EU council. However, it never came into force because some countries refused to sign. Finally, ratified by all the member states, the first Insolvency Law was enacted in 2002.

Nevertheless, the general economic crisis which affected European countries in the period between 2009-2011, together with the huge number of firms that went bankrupt, expressed the inadequacy of the current insolvency law (Akšamović, 2018). This situation has led to further consultations, ended in May 2015 with a new insolvency regulation 2015/848, commonly denoted as the Recast Insolvency Regulation, which came into force two year after, in 2017.

The new regulation does not differ substantially from the previous one, since it includes the same fundamental premise, but it broadens and strengthens the current framework (Akšamović, 2018). One of the objectives of Recast Insolvency Regulation is to shift the focus away from liquidation towards encouraging viable business to restructure at the early stage to prevent insolvency (Stones, 2017).

As stated in European Commission press release (2014), “the modernized regulation” will bring:

- A broadened scope: The rules will cover a broader range of commercial and personal insolvency proceedings, such as the so-called Spanish scheme of arrangement, the Italian reorganization plan procedure and the Finnish consumer insolvency procedures. Overall, the reform will allow 19 new national insolvency procedures to benefit from the Regulation.
- Legal certainty and safeguards against bankruptcy tourism: If a debtor relocates shortly before filing for insolvency, the court will have to carefully look into all circumstances of the case to see that the relocation is genuine and not abusive.
- Interconnected insolvency registers: Businesses, creditors and investors will have easy access to any national insolvency register European e-Justice Portal
- Increased chances to rescue companies: The new rules avoid secondary proceedings in other Member States being opened, while at the same time guaranteeing the interests of local creditors. It will be easier to restructure companies in a cross-border context.
- A framework for group insolvency proceedings: With increased efficiency for insolvency proceedings concerning different members of a group of companies, there will be greater chances of rescuing the group as a whole

In order to apply the Recast Insolvency Regulation there are three conditions that must be fulfilled cumulatively:

a) Firstly, proceeding must be collective.
b) Secondly, proceedings can be opened only in connection to the debtor’s insolvency and not on other grounds (Welles, 2006). This doesn’t mean that the debtor must be insolvent. Recast Insolvency Regulation may be applied in case when there is only likelihood of insolvency but only if the purpose of such pre-insolvency proceeding is to avoid the debtor’s insolvency or the cessation of the debtor’s business activities[1]. Therefore, insolvency, pre-insolvency and reorganization proceedings should fit within scope of Article 1of the Recast Insolvency Regulation.
c) Thirdly, the proceeding should entail the appointment of insolvency practitioner, such as for example “liquidator” and must be subject to control or supervision by the court.

The Recast Insolvency Regulation adopts, as included in the previous law, the same concept of COMI, which is the debtor’s Center of Main Interest, in order to determine which court of the member state is responsible for opening a main and unique insolvency procedure.

[1] Article 1 par.2 Recast Insolvency Regulation

Generally, COMI is "in the place where debtor conducts the administration of its interests on a regular basis and which is ascertainable by third parties"[2]. This rule aims to avoid abusive forum shopping, which occurs when companies seek for a more favorable jurisdiction in order to prevent an insolvency proceeding, or to have a friendly one (Akšamović, 2018).

Moreover, the law includes the possibility for a secondary proceeding which can be opened in country in which debtor has an "establishment" within the territory of that State. The purpose of the secondary proceeding is to protect local creditors from the main proceedings while supporting at the same time the operation of the proceeding (Akšamović, 2018).

Certainly, the new regulation contributes to improve efficiency and effectiveness of cross-border insolvency proceedings. However, the unification of insolvency laws among European countries is still a matter of concern for the EU commission (Akšamović, 2018).

1.3.2 The Bankruptcy Regime in Italy

With the first Italian Bankruptcy law (R.D. 267/1942 "The Royal Decree"), Bankruptcy was denoted as a permanent negative state and the recovering was considered difficult to implement and socially unacceptable. Consequentially, the legal system was designed to punish the debtor, with the liquidation of its assets, rather than facilitate its recovery and reorganization (ICLG, 2018). The idea of the distressed enterprise as a social threat needed to be punished remains until the late 20th century (Manganelli, 2010).

As a matter of fact, the *Ordinary Bankruptcy Proceedings*, set forth in the Royal Decree were essentially liquidation proceedings, like Chapter 7 in U.S. The petition for bankruptcy may be filed by the debtor itself (voluntary bankruptcy) or filed by the creditors of the debtor or by the public prosecutors (involuntary bankruptcy). After the filing of a bankruptcy petition, a debtor loses control over its assets (an Ordinary Bankruptcy Proceeding is a "debtor-not-in possession" proceeding), and a bankruptcy court-appointed receiver administers the proceeding under the supervision of the bankruptcy court. The proceeds from the sale are then distributed to creditors. (Manganelli, 2010).

However, the widely publicized failure of several Italian corporations, such as the collapse of the Parmalat Group (2003) and the insolvency of national air carrier Alitalia (2008), highlighted the inadequacies of the Italian bankruptcy laws in dealing with such large

[2] Article 3 (1) of the Recast Insolvency Law

corporate bankruptcies (Manganelli, 2010). As a result, the bankruptcy system and its objective needed to be changed.

The "Marzano Law" in 2003, was the starting point for the improvement of the system. For the first time, the bankruptcy proceeding was aimed to encourage the recovery of a debtor company through a composition agreement between the debtor and its creditors (Manganelli, 2010). The law especially refers to large corporation by allowing for more flexible proceedings (Belhocine, Garcia-Macia & Garrido 2018). An alternative to the ordinary liquidation procedure was introduced with the *in-bankruptcy composition* (Concordato Fallimentare) in which a creditor or a third party can propose a plan aimed at full or partial reimbursement of the creditors (ICLG, 2018).

Afterwards, between 2005 and 2013, the Italian discipline on business crises was the subject of several reforms, which tried to strengthen the bankruptcy reorganization, particularly in its function as an institution designed to favor the continuity of companies in a non-irreversible crisis (Castelli, Micucci, Rodano and Romano, 2016). Moreover, the peculiarity of the Italian context is the presence of the "*extraordinary administration*" only for great-sized commercial undertakings with the aim of carrying on, restarting or converting the business activities and to protect employment.

A new bankruptcy agreement to deal with insolvency crisis was introduced with the Law number 3 of the 27 January 2012. The need for a normative intervention arises due to the disparity treatment for the non-professional creditors category which was not able to estimate the probability of bankruptcy of such debtors. Non-professional creditors indeed, did not have possibility to access bankruptcy prediction models and thus, to take preventive measures. (D'amore 2018). Therefore, the law 3/2012 is extremely important for the little-medium size firms, which often do not have enough resources to buy a professional consulting service or proper instruments to estimate and control the probability of failure.

The law finally introduced the pre-insolvency proceedings. The provision outlines two procedures: a bankruptcy composition with creditors or *pre-bankruptcy composition* (Concordato Preventivo) and a *debt restructuring agreement*. Both the procedures are aimed to avoid unnecessary economic collapse with the frequent impossibility to satisfy creditors (Deloitte, 2017). The composition with creditors requires the supervision of the court and the approval by the majority of the creditors.

Differently, regarding the debt restructuring agreement, the law considers the instrument of the agreement with the creditors, proposed by the debtor, based on a debt restructuring plan that assures the regular payment of the creditors (Art. 182 bis of the Bankruptcy law). With respect to the latter, the plan may also allow for a payment moratorium, provided that the plan is suitable for guaranteeing payment at the end of the new depletion and the proceeding is not entrusted to a liquidator appointed by the judge. To obtain the agreement is necessary to reach 70% (60% after the decree 179/2012) of the creditors' acceptance[3]. The court is involved in the final phase for the approval, but has no duty of supervision over the execution of the agreement (ICLG, 2018)

The proceeding involves a dedicated body for the settlement of the *over-indebtedness* crisis, providing assistance to the debtor aimed at overcoming the liquidity crisis. Over-indebtedness means the situation of persistent imbalance between the obligations assumed and the assets readily to be liquidated to deal with them, which determines the significant difficulty in fulfilling one's obligations, or the definitive inability to perform them regularly[4].

The law-decree dictates a series of provisions affecting the plan, including the possibility of non-full payment to privileged creditors. By contrast, as regards to the creditors outside the agreement proposed by the debtor, the decree consider them sufficiently protected by the court judgement on the appropriateness of the restructuring agreement rather than the liquidation of the debtor's assets.

Finally, the latest improvement of the Italian Bankruptcy law was on October 2017, when Law no. 155 was published on the Italian Official Gazette, setting forth the "Delegation to the government for the reform of corporate crisis and insolvency law" (the "Delegated Law").

One of the major changes include the replacement of the word "bankruptcy" with the term "judicial liquidation" for the Italian insolvency panorama. The reason of this lexical intervention relies on the negative connotation entailed in the word "bankruptcy" and the willingness to change the approach from the past. As a matter of fact, when a firm was declared bankrupted, it was automatically linked with an antisocial and illegal behavior. Again, the purpose is to encourage the recovery of the distressed firm rather than the punishment with a mere liquidation of its assets. Moreover, the law wants to change the public's perception from that of a bankruptcy proceeding directed against the person of the debtor to that of a proceeding of judicial liquidation directed towards their assets and a consequent shift in emphasis onto the object of the proceeding, rather than the subject (Bennocci, 2018).

[3] Camera.it Law 3/2012 - *Composizione delle crisi da sovraindebitamento*
[4] Law 3/2012 art. 6

The law promotes the use of out-of-court settlement of the crisis, both through the introduction of an "alert procedure" to enable business distress to emerge earlier and through the facilitating of access to either reorganization plans or debt restructuring agreements. For this new "judicial liquidation", the reform law delegates the government to adopt a sign procedure to determine whether a company is in the state of "crisis" or "insolvency" to verify the economic collapse Following this first step, the proceeding could evolve in a different way, depending on its mode (whether agreed or compulsory) and purpose (whether it was to lead to composition with creditors or liquidation). The provision also compresses the "pre-bankruptcy composition with creditors" by providing only an arrangement "on a going concern basis". It changes the regulations regarding the settlement of the over-indebtedness crisis and other special proceedings. It provides new directions regarding the crisis and insolvency of business groups and the identification of the competent judicial authorities by also considering their level of specialization (Bennocci, 2018)

1.3.3 The Financial Services Industry

A considerable body of literature concerning corporate financial distress and bankruptcy investigation has been developed using companies belonging to the manufacturing as the sample of their studies. For instance, we can mention the work of Darayseh et al. (2003) which focused on forecasting corporate failure for manufacturing industry using firms specifics and economic environment with logit analysis; Appiah and Abor (2009) with the same purpose provided empirical evidence from the UK manufacturing sector; Paolone and Pozzoli (2017) investigate the bankruptcy probability using a sample of Italian manufacturing companies and many other scholars mainly focused their study on the manufacturing and industrial sector while, by contrast, the financial service industry has not been widely taken in consideration for similar studies.

Probably, the most reasonable explanation is that the manufacturing sector experienced an economic recession after the big crisis of 2008 and the industrial sector, in general, has the greatest percentage of business failure. Otherwise, as perceived by Zaychenko et al. (2019), bankruptcy prediction models may operate with more incomplete and unreliable data provided by the managers. And finally, maybe due to their relevance in the overall economy, since banks and other financial services institutions provide loans and manage savings of thousands of clients, from companies to individual, they are often not allowed to fail. However, this is very often the case of listed companies. The regulators consider the concept of "too big to fail" (TBTF), the logic of which is that the failure of a large financial institution will have ramifications for other financial institutions and therefore the risk to the economy would be enormous (Helwege, 2009).

Over the years, the financial sector has suffered several crises that have led to an overall instability and consequentially, a lack of trust in financial institutions. The “Tulips Bubble” in 1637 was the first financial crisis in the history, triggered by the use of financial instruments for speculative purposes. Then, the big disaster of ’29, started in the USA shocked the world economy, leading to the failure of an enormous number of companies. Afterwards, at the end of the 90’s, many financial crises affected emerging markets such as Mexico, Brazil, Argentina and Southeast Asia, characterized by the presence of growing imbalances both in public finances and in foreign relations. Yet, the most popular financial crisis occurred in 2007 for the use of the Subprime mortgages. Indeed, since 2003 began to significantly increase the provision of high-risk mortgages, that is, mortgages were provided to people who would not have been able to provide warranties and to repay. Moreover, the factors that have stimulated the growth of subprime mortgages are attributable, among other things, to the dynamics of the US real estate market and the development of securitization. This crisis started in USA and in 2010 involved many countries in the Euro area. Many European credit institutions have experienced serious difficulties and have been saved by public interventions.

In 2011, the effects of the crisis arrived in Italy with its serious consequences, leading to a period of instability and uncertainty for the overall economy of the country.

As a matter of fact, considering just the Italian scenario, in the five-year period from 2013 to 2018, around 1096 unlisted companies belonging to the financial services sector filed for bankruptcy. This information resulted from AIDA financial database for Italian companies and, from my personal point of view, it worth to be analyzed and investigated by using an appropriate model for bankruptcy prediction.

For this reason, I decided to contribute to the literature of bankruptcy prediction studies by using a sample of companies belonging to the financial services sector, as the basis for the empirical analysis presented in the third chapter of this paper.

CHAPTER II

Bankruptcy Prediction Models

In this chapter, I will analyze the existing methodologies of financial distress prediction, by reviewing the most used models in the literature. Nevertheless, the panorama of related studies is enormous, and the models we will discuss are only a fraction of the total amount of bankruptcy literature.

In order to better organize the material, we will divide the methodologies in three macro groups: accounting-based models, market-based models, and mixed (hybrid) models. After a general overview of the existing methods, we will focus our attention on the accounting-based group. Firstly, because accounting-based techniques are the most popular used by scholars due to their practicality. Secondly, because in the next chapter we will use an accounting-based model for our empirical study.

Successively, we will introduce alternative bankruptcy prediction techniques based on artificial intelligence that somehow provide advantages but require much more effort for the implementation.

Finally, we will discuss the relevance of cash flow-based ratios compared to the traditionally used accrual accounting-based ratio. As a matter of fact, this concept provides the basis for the development of our empirical study presented in Chapter III.

2.1 Comparison of the methodologies

Several bankruptcy predictions models have been used in the past century. Univariate analysis progressed to Multiple Discriminant Analysis. Logit/Probit analysis came next. Finally, artificial intelligence tools are the most recent bankruptcy prediction techniques.

Bankruptcy prediction models can be roughly classified in three categories: accounting-based models, market-based models and mixed models. A common characteristic to each framework is the presence of two main phases: at first, the models use a quantitative analysis to estimate the probability of failure. Then, the firm is assigned to a risk group. Precisely, the second phase implies the decision to collocate the firm in the risky or non-risky group or bankrupt vs non-bankrupt (Mousavi et al., 2015).

2.1.1 Accounting-Based Models

Accounting-based models employed financial ratios derived from the firm's income statement and balance sheet. Over the last 50 years, the majority of the models were designed with financial and accounting data (Dimitras et al., 1996). In particular, these models use financial information measured by profitability, liquidity and solvency ratios, in order to assess the bankruptcy risk for the firm and evaluate its financial stability. These indicators are generally compared to a benchmark ratio representing the condition of soundness (Paolone & Pozzoli, 2017). Accounting based models can be divided into three main subcategories: namely Discriminant analysis and Regression model for categorial variables and survival analysis (Mousavi et al. 2015) that we are going to further analyze in the following paragraphs.

The greatest advantage of accounting-based models is that financial information is easily available and observable. Moreover, financial ratios are calculated in a standardized way due to the strict regulatory framework which dictates standards to follow when presenting the financial statements (Du jardin, Veganzones and Séverin, 2017). However, these models suffer from several drawbacks: The most noted limitation is the over-reliance on financial statements data that measure past performance of the firm, because sometimes it could be difficult to provide a future prospective based only on a backward looking (Hillegeist et al. 2004). By contrast, Agarwal and Taffler (2006) considered the nature of financial distress as a result of several years of negative performance and consequentially, historical financial information can be suitable for failure prediction.

Another limitation of these models is that the asset value recorder in the financial statement, noted as book value, may be different from the actual market value, which is, the real current value of the asset in the market. Therefore, the use of accounting information may lead to inaccurate evaluation of the firm's financial soundness (Paolone & Pozzoli, 2017) (Agarwal and Taffler 2008).

Finally, financial statements are subjected to different *earnings management* techniques. Du jardin, Veganzones and Séverin (2017) define earnings management as a set of financial reporting practices that are performed within the limits of a given regulatory framework. Which means that managers can show levels of earnings that do not reflect the reality, depending on the goals they have decided to pursue (Watts and Zimmerman 1990). More precisely, distressed firms tend to increase their perceived value by engaging in upward earnings behavior to hide their weaknesses, whereas healthy firms tend to do the opposite and engage in behavior that downplays their earnings, so as to minimize their level of taxation (Du jardin, Veganzones and Séverin, 2017). By far, distressed firms have more incentive to manipulate their accounts. Earnings generally reflect the firm's performance. Therefore, bankruptcy models can lose their predictive accuracy due to the potential "manipulation" of annual records which may affect financial variables.

Three types of manipulations are traditionally studied in the literature and are applied to revenue, expense and bad debt (Peasnell et al. 2000). Revenue manipulation consists in granting clients higher delays of payment than usual. From a technical point of view, this manipulation is achieved using an increase in sales and in receivables (and hence an increase in total accruals). Expense manipulation is intended to delay the recognition of an expense that reduces payables. Finally, bad debt manipulation is used to under-estimate provisions that should be made to cover the risk associated with such debt, and this manipulation leads to an increase of net debt, and consequently to an increase in total accruals.

In addition to this, Hillegeist et al. (2004) argue that since the accounting statements are prepared on a going-concern basis, they are, by design, of limited utility in predicting bankruptcy.

Despite the previously stated drawbacks, accounting based models dominate the panorama of bankruptcy prediction. Beaver (1966) was among the first who use accounting information to develop a bankruptcy prediction model and few years later, Altman (1968) employed a multiple discriminant analysis (MDA) and Ohlson's (1980) develops a logit model using accounting information. They investigate the probability of failure by analyzing a large number of financial ratios on a sample of failed and non-failed firms.

2.1.2 Market-based Models

Market-based models use information derived from the market i.e., share prices (Muvingi, et al., 2015). Pioneers of this category of models were Black and Scholes (1973) and Merton (1974) using option pricing methods. These methods observe stock prices and their volatility to deliver a risk assessment. Specifically, they observe the market value of the assets and define corporate default when this latter value becomes below the book value of liabilities (the default point) (Muvingi, et al., 2015). This market-based approach serves as the building block of several credit risk models commonly used in practice (e.g. that of Moody's KMV) (Li & Miu, 2010).

According to Beaver (2005), market-based models are valuable in predicting bankruptcy because, in efficient markets, stock prices reflect all the information included in the financial statement but also information not included in the accounting documents. Moreover, market prices update constantly, and they are available on a daily basis (however, this is valid only for large corporations), while financial statements only on a yearly basis. Additionally, market variables allow for the estimation of volatility (e.g. standard deviation of earning per share) (Paolone & Pozzoli, 2017), which is a main indicator of risk. Indeed, market prices reflect future expected cash flows, and hence should be more appropriate for prediction purposes. Finally, market variables are unlikely to be influenced by firm accounting policies (Agarwal and Taffler 2008).

However, the Merton model is a structural model based on strong assumptions. For instance, it assumes that the natural logarithms of stock prices are normally distributed (Mousavi et al., 2015). It also considers that a firm has non-differentiated debts, only zero-coupon-bond loans and all liabilities with 1-year maturity (Agarwal and Taffler 2008).

Not surprisingly, the empirical evidence on the performance of market-based models is mixed (Agarwal and Taffler 2008). From one side, Kealhofer (2003) and Oderda et al. (2003) suggest that such models outperform credit ratings, and in their empirical studies Hillegeist et al. (2004) find out that Black-Scholes-Merton structural models are up to 14 times more informative about the probability of bankruptcy than poorly performing accounting-based methods (Reisz and Perlich, 2007). On the other side, Campbell et al. (2006) find such market-based models have little predictive power after controlling for other variables. Similarly, Reisz and Perlich (2004) find that (backward-looking) accounting-based measures are most relevant for short-term (1 year) bankruptcy prediction, while (forward-looking) market-based structural models are best suited for medium- and long-term default predictions (3 to 10 years).

2.1.3 Hybrid Models

Hybrid models, as the one proposed by Shumway (2001), use both accounting ratio and market-driven variables to improve the alternative bankruptcy forecasts models. In particular, the “hazard model” of Shumway (2001) includes two of the accounting ratios (net income to total assets and total liabilities to total assets) previously used by Altman (1968) and Zmijewski (1984) and three market variables (market size, past stock returns, and the idiosyncratic standard deviation of stock returns) to identify bankrupt firms. Other less popular contributions to this vein of hybrid models were given by Campbell et al. (2008), CHS in the same year, Li and Miu (2010), and supported by Miller (1998), Kealhofer (2003), Löffler (2007) and Mitchell and Roy (2008), as they conclude that combining various failure prediction models improves the prediction of default over the use of a single measure.

Despite extensive criticism, Agarwal and Taffler (2008) conclude that we do not have enough evidences of the superior performance of market-based models over the accounting-based techniques. They showed that the accounting-based approach produces significant economic benefit over the market-based approach. In fact, traditional approaches still dominate risk assessment practices, as suggested by Paolone and Pozzoli (2017) the accuracy rate of the model of Altman (1968) was 79%, and no market-based model reach this percentage.

2.2 Accounting-based models

The intense contributions to the literature given by Beaver (1966), Altman (1968), Ohlson (1980), Zmijewski (1984) and many others, fall into this category of accounting-based bankruptcy prediction techniques. They use critical financial ratios derived from accounting information to detect corporate financial difficulties. Accounting-based model can be further into three subcategories (Mousavi et al., 2015): namely, discriminant analysis models, regression models for definite variables and survival analysis models.

2.2.1 Discriminant Analysis

Discriminant Analysis (DA), first proposed by Fisher (1938) is a collection of classification methods which aim at separating observations into two or more groups so as to maximize within-group similarity and minimize between-group similarity, where "similarity" is measured by some sort of distance between observations (Mousavi et al., 2015). In other words, the purpose of discriminant analysis is to find the linear combination of ratios which best discriminates between the groups which are being classified (Deakin, 1972), namely failed and non-failed firms. Through the discriminant analysis the bankruptcy prediction models derive an index and a cutoff point of the index (Blum, 1974). The index is given by the computation of the financial variables delineated by the model for each company in the sample studied. The sum of the variables gives an index score which must be compared to cutoff point. All companies with index scores above the critical point are predicted to succeed and all companies with scores below are predicted to fail (Blum, 1974).

Beaver (1966), was the first who developed a Univariate statistical analysis by investigating the predictive ability of each accounting ratio, one at a time. This model presented limitations that Altman (1968) tried to fix by using a Multiple Discriminant Analysis (MDA) where a set of economic and financial ratios were considered simultaneously. Deakin (1972) replicated the Beaver study and he examined the linear combination of the same ratios used by Beaver, which best predicted potential failure in the five years prior to failure. The results showed that multiple discriminant analysis may be more suited for short-run financial distress prediction (Lin, 2009). Following the same path, Blum (1974) compared 115 failed firms and 115 non-failed firms from 1954 to 1968. The failed firm group and non-failed firm group are matched by industry, sales, employees, and fiscal year. Blum used discriminant analysis and 12 variables to build the financial distress prediction model. The results showed that the correct classification rates are above 70%. However, discriminant analysis techniques present limitations that scholars tried to overcome in the following years by delivering new bankruptcy prediction models.

2.2.2 Probabilistic Models

Regression Models or probabilistic models include the Logit and Probit models. Ohlson (1980) criticized the restrictive assumption of the discriminant analysis technique and developed a logistic regression (Logit model) to estimate the probability of default. Ohlson (1980) in particular, did not agree with the assumption of normally distributed predictors and he provide a binary outcome (Waqas & Rus, 2018). Similarly, the Probit model of Zmijewski (1984) used financial ratios that measured firm performance, leverage, and liquidity to estimate a probability value. The ratios were not selected on a theoretical basis, but rather based on their performance in prior studies.

The advantage of the Logit and Probit models is the outcome as a definite probability value of bankruptcy from 0 to 1 and the relative simplicity of interpretation. This is the reason why these two models are widely used in literature (Waqas & Rus, 2018).

We will further examine these most popular models in the following paragraphs.

2.2.3 Survival Analysis

Survival Analysis models differ from discriminant analysis and regression models since they introduce the element of time to event in the analysis (Mousavi et al., 2015). As a matter of fact, the previous categories of models are static, they do not consider firm performance or risk level over time. Shumway (2001) proposed a discrete-time hazard model to overcome this limitation. He criticized static and single period models which might deliver incorrect and biased coefficient estimations of bankruptcy probability, because they do not consider that firms change over time. Additionally, Beck, Katz, and Tucker (1998) demonstrate that the standard errors of such static models will be understated. Following this suggestion, also Hillegeist et al. (2004) developed a discrete-time hazard model which they believe would be best to analyze data that consists of binary, time-series, and cross-sectional observations, such as bankruptcy data.

However, these models are in between the two macro categories of accounting-based and market-based models, since they belong to the hybrid or mixed category. Indeed, Shumway (2001) starts from the accounting ratios, but he found that some of them are not significant for the study, while he believes that market size, past stock returns, and idiosyncratic returns variability are all strongly related to bankruptcy and, the combination of accounting ratios and market variables can lead to a more accurate forecasting.

2.3 Beaver's Univariate Analysis

Since 1930, a considerable number of studies has been focused on the relationship between financial ratios and bankruptcy (Bellovary et al., 2007).

In 1966, William H. Beaver, took the flow of studies a step further. He compared the mean values of 30 ratios of 79 failed and 79 non-failed firms in 38 industries during the time period of 1954–1964, and he tested the individual ratios' predictive abilities in order to discriminate between bankrupt and non-bankrupt firms (Bellovary et al., 2007). Beaver's model is denoted as univariate analysis since he analyzes one ratio at time. He found that these ratios were significantly lower for distressed firm when comparing to sound firms, with the value worsening as the year of failure approached. Moreover, by analyzing the financial statements he concluded that the significant differences in ratios of distressed and non-distressed firms can be observed for up to 5 years before the bankruptcy (Paolone & Pozzoli, 2017). Among these ratios, Beaver (1966) found that Cash Flow to Total Debt had the highest predictive ability, followed by the Net Income to Total Assets ratio, then the Total Debt to Total Assets ratio and finally the three liquid-asset ratios.

More precisely, as regards to the sample, the financial-statement data of the firms were obtained from *Moody's Industrial Manual* for five years prior to failure. The asset-size range was 6 million to 45 million dollars, and the mean asset size was approximately 6 million. The comparison between one failed and one non-failed firms can be meaningful only if the two firms are in the same industry and if they have the same asset-size, because these variables might blur the relationship between ratios and failure. Therefore, each failed firm has a non-failed "mate" in the sample.

The 30 ratios were selected according to the following criteria:

- Popularity: frequency of appearance in the literature
- Performance in previous studies
- The concept of "Cash flow": liquid-asset-flow

Table 2.1. List of Ratios

Group I (Cash-flow ratios)	*Group V (Liquid-asset to current debt ratios)*
1. Cash flow to sales	1. Cash to current liabilities
2. Cash flow to total assets	2. Quick assets to current liabilities
3. Cash flow to net worth	3. Current ratio (current assets to current liabilities)
4. Cash flow to total debt	*Group VI (Turnover ratios)*
Group II (Net-income ratios)	1. Cash to sales
1. Net income to sales	2. Accounts receivable to sales
2. Net income to total assets	3. Inventory to sales
3. Net income to net worth	4. Quick assets to sales
4. Net income to total debt	5. Current assets to sales
Group III (Debt to total-asset ratios)	6. Working capital to sales
1. Current liabilities to total assets	7. Net worth to sales
2. Long-term liabilities to total assets	8. Total assets to sales
3. Current plus long-term liabilities to total assets	9. Cash interval (cash to fund expenditures for operations)
4. Current plus long-term plus preferred stock to total assets	10. Defensive interval (defensive assets to fund expenditures for operations)
Group IV (Liquid-asset to total-asset ratios)	11. No-credit interval (defensive assets minus current liabilities to fund expenditures for operations)
1. Cash to total assets	
2. Quick assets to total assets	
3. Current assets to total assets	
4. Working capital to total assets	

Beaver (1966) considered the firm as a reservoir of liquid assets, supplied by inflows and drained by outflows. When reservoir is exhausted the firm become insolvent, in the sense that it is unable to pay its obligations as they mature, and insolvency lead to failure.

Consequentially, in order to explain the relationship between the ratios and the failure, he derived four proposition which refer to four important concepts of this liquid-assets-flow model:

1. The larger the reservoir, the smaller the probability of failure.
2. The larger the net liquid-asset flow from operations (i.e., cash flow), the smaller the probability of failure.
3. The larger the amount of debt held, the greater the probability of failure.
4. The larger the fund expenditures for operations, the greater the probability of failure.

After the computation of the 30 ratios for each firm, Beaver observed the differences in the mean value to prove the lower cash flow and the smaller reservoir of liquid assets for failed firms compared to non-failed firms. The result indicates that the limited ability to pay the obligations, to be insolvent and thus, to fail, can be predicted through the analysis of the relevant accounting ratios. Moreover, the prediction of failure can be effective since these above-mentioned differences in the mean value might be visible from up to 5 years before the actual default.

Additionally, Beaver (1966) conducted a Dichotomous Classification Test to make a prediction of whether a firm is either failed or not failed. A specific ratio, one at time, is compared to its benchmark ratio, which is the optimal cutoff point, and if a firm's ratio is below (or above, as in the case of the total debt to total-assets ratio) the cutoff point, the firm is classified as failed. If the firm's ratio is above (or below, for the total debt to total-assets ratio) the critical value, the firm is classified as non-failed.

In general, it is helpful to define two types of prediction error when evaluating the power of the bankruptcy models (Lennox, 1999): A type I error occurs when a company fails but is predicted to survive; a type II error occurs when a company survives but is predicted to fail. Clearly, the type I and type II error rates depend on the number of companies predicted to fail. The higher (lower) the number of companies predicted to go bankrupt, the smaller (larger) is the type I error rate and the larger (smaller) is the type II error rate. The number of predicted bankruptcies depends on the cut-off probabilities chosen for the models. For example, if the cut-off is equal to 0.1, a company for which the expected probability of bankruptcy exceeds 10% is predicted to go bankrupt, whereas a company for which the expected probability of bankruptcy is less than 10% is predicted to survive. One can therefore increase the number of companies predicted to fail by reducing the cut-off probability. Of course, the ratio cannot classify failed and non-failed firm with equal success (Beaver, 1966). Generally, in each year before failure type I error is greater than type II error. Indeed, type II error is stable over the five-years period, while type I error increase as the time before failure increase.

2.4 Altman's Multivariate Analysis

Although highly contributive, the previous studies were essentially based on univariate analysis which may leads to misclassification. For instance, a firm experiencing profitability/solvency problem may be classified as potential bankrupt because the related ratio resulted to be below the cutoff point. However, the same firm may own consistent level of liquidity that can be used to avoid the failure. Therefore, the reliability of these model for predicting business failure was questionable.

For this reason, Altman (1968) developed a predictive model that considers multiple variables at the same time. The Multiple Discriminant Analysis (MDA) is a linear combination of financial indicators, aims at classifying an enterprise as bankrupt or non-bankrupt. The indicators of the firm's characteristics are presented through financial ratios which best predict corporate distress and bankruptcy. Altman (1968), suggests specific discriminant coefficient to each accounting ratio which represent the appropriate weight of each characteristic on the firm's performance.

The sample object of the study was composed by 33 failed firms and 33 non-failed firms similar in size and industry, during the period 1946-1965. In particular, these firms belong to the manufacturing sector with the size ranging from \$0.7 million to \$25.9 million. In this sample was not considered both the small firms (under \$1 million in total assets) and the very large companies.

As beaver did, he collects the financial statements of the firms and he selects 22 potentially useful ratios. The ratios were grouped into five main categories: liquidity, profitability, leverage, solvency and activity ratios. He picks the five most relevant ratios according to (1) observation of the statistical significance of various alternative functions including determination of the relative contributions of each independent variable; (2) evaluation of inter-correlations between the relevant variables; (3) observation of the predictive accuracy of the various profiles; and (4) judgment of the analyst. By multiplying each discriminant coefficient to its relative ratio, the statistical function provides an overall score, the so-called Z-score, which can be used to discriminate between the two groups of firms.

The form of the discriminant function is:

$Z = A_1 X_1 + A_2X_2 + A_3X_3 + A_4X_4 + A_5X_5$

Where:

- Z is the score used to classify or predict the firm into one of the groupings.
- $A_1, A_2, ..., A_n$ are the discriminant coefficients.
- $X_{1,} X_2, ..., X_n$ are the set of predictor indicators (ratios).

The final function completed with the discriminant coefficient is:

$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$

The five ratios selected by Altman are the following:

X_1= *working capital/total assets*. This ratio is a measure of the liquidity asset of the firm relative to the total capitalization. The working capital is the difference between current assets and current liabilities. Current assets are liquid cash, and assets convertible to cash within one year. It includes stocks, cash, and cash equivalents available with the company, marketable securities, accounts receivables, inventories, and prepaid expenses. Current liabilities include accounts payable, notes payable, current maturities of deposits taken, and accrued liabilities (Paolone & Pozzoli, 2017). Among the liquidity ratios, working capital to total assets is the most powerful for prediction purposes. Indeed, a firm experiencing consistent losses will result to have negative working capital and is likely to experience problems paying off its obligations.

X_2= *retained earnings/total assets*. The ability to reinvest earnings and to self-financing is measured through this ratio. The age of a firm is implicitly considered in this ratio (Altman, 1977). Clearly, a young firm is likely to have low retain earnings to total assets since it has not time to build up an history of profitability. Therefore, this ratio supports the theory that firms in the first years of their life are more likely to go bankrupt. In addition, the RE/TA ratio indicates the leverage degree of a firm. Indeed, high RE, relative to TA, means that firms have financed their assets through retention of profits rather than utilized large debt.

X_3= *earnings before interests and taxes/total assets*. This ratio is an indicator of the productivity of the firm’s assets without considering any tax or leverage factors. The relevance of this ratio relies on the important to measure the assets’ ability to generate profit which indicates the fair value of the firm’s assets.

X_4= *market value of equity/book value of total debt*. Equity value is combined by the market value of all share stocks, while the denominator is the sum of short- and long-term liabilities. The ratio shows, if a firm were to becomes insolvent, how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets. This ratio has been slightly modified by Altman respect to one previously utilized by other scholars since it adds a market value dimension.

X_5= *sales/total assets*. The capital-turnover indicates the ability of the assets to generate sales. This measure is important and entails high discriminating power because it shows how well management handles competition and it reflect the ability to grow market share.

In order to test the discriminant ability of the variables selected for the model he conducts the "F" test, based on the observation of the differences in the mean value of the ratios between the two groups. The results are shown in **Table 2.2**.

Table 2.2 Significant Test of Altman (1968)

Variables	Bankrupt Group Mean	Non-Bankrupt Group Mean	F Ratio
	N=33	N=33	
X1	-6,1%	41,4%	32,60*
X2	-62,6%	35,5%	58,86*
X3	-31,8%	15,3%	26,56*
X4	40,1%	247,7%	33,26*
X5	150,0%	190,0%	2,84

*Significant at the 0,001 level

$F_{1,60}$ (0.001) = 12.00

$F_{1,60}$ (0.01) = 7.00

$F_{1,60}$ (0.05) = 4.00

Variables X1 through X4 are all significant at the 0,001 level while variable X5 does not shows significant difference in the mean values between the two groups. However, this test is based on univariate basis and do not considers the interactions between the variables.

Afterwards, Altman investigates the individual contribution of each variable to the total discriminating power of the model and their interaction using the scaled vector (**Table 2.3**).

The scaled vector is computed by multiplying corresponding elements by the square roots of the diagonal elements of the variance-co-variance matrix.

Table 2.3 Relative Contribution of The Variables

Variables	Scaled Vector	Ranking
X1	3,29	5
X2	6,04	4
X3	9,89	1
X4	7,42	3
X5	8,41	2

The table shows that the profitability ratio X3 contributes the most, followed by the X5 which interestingly, at the univariate level resulted to be insignificant.

Altman (1968), at first tested its model on the initial sample of 66 companies. The result was an accuracy of 95% in classifying bankrupt and non-bankrupt firm to their actual group. The rate of misclassification was only 6% for Type I error (classifying a bankrupt firm as a non-bankrupt) and 3% for type II error (classifying a non-bankrupt firm as bankrupt). Moreover, finding suggests that bankruptcy can be accurately predicted up to two years prior to actual failure with the accuracy diminishing rapidly after the second year. Indeed, as the lead time increases, the relative predictive ability of any model would decrease.

Then, Altman used two new samples: one of 25 bankrupt firm and he correctly classify 24 (96%). The second one of 66 non-bankrupt firms in manufacturing which suffered losses and net income and the discriminant model correctly classified 79% of the sample firms.

Altman concluded that firms with the Z-scores greater than 2.99 are classified in the safe zone as non-bankrupt and those less than 1.81 fall into the distress zone as bankrupt. The firms that score between 1.81 and 2.99 are in the "zone of ignorance" or "grey zone" due to the possibility of error classifications.

- $Z < 1.80 \rightarrow$ Distress Zone
- $Z > 2.99 \rightarrow$ Safe Zone
- $1.8 < Z < 2.99 \rightarrow$ Grey Zone

The multiple discriminant analysis of Altman and its Z-score remains the most powerful and effective bankruptcy prediction model and several practical applications were suggested. For instance, the model is useful in business credit evaluation, internal control procedures and investment guidelines.

2.4.1 Altman's Revised Z-Score

The original Altman's Z-score model (1968) was revised many times and the coefficients were adapted to different situations (Altman, 1983, 2002; Altman, Hartzell, Peck, 1995). As a matter of fact, the application of the original Altman's model was limited because the model was based only on publicly held manufacturing companies, whose financial statements and market prices were obtainable. Therefore, Altman (1977) re-estimates the model by substituting the market value of equity with the book value and by changing the discriminant coefficient to make it suitable for private companies.

The final function resulted to be:

$Z' = 0.717\ X_1 + 0.847\ X_2 + 3.107\ X_3 + 0.420\ X_4 + 0\ .998\ X_5$

Where:

- *X_1 = Working capital/Total assets*
- *X_2 = Retained Earnings/Total assets*
- *X_3 = Earnings before interest and taxes/Total assets*
- *X_4 = Book value of equity/Book value of total liabilities*
- *X_5 = Sales/Total assets*
- *Z' = Overall Index*

In the revised model, the boundary level for discriminate between bankrupt and non-bankrupt also changed:

- $Z < 1.23$ → Distress Zone
- $Z > 2.90$ → Safe Zone
- $1.23 < Z < 2.90$ → Grey Zone

During the following years, Altman, Hartzell and Peck (1995) introduce the Z'' Score for non-US, emerging markets companies and non-manufacturing companies.

The variables of the Z"-Score were the same as the Z'-Score model with the exclusion of the sales/total assets, activity ratio (X_5) in order to filter the function from the possible distortion related to the sector and country. The weighted coefficients thus have different values:

$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$

When computing the Z" Score for emerging countries, Altman, Hartzell and Peck proposed adding a constant (+3.25) in order to standardize the results so that scores equal or less than 0 would be equivalent to the default situation. Emerging markets credits may initially be analyzed in a manner similar to that used for traditional analysis of U.S. corporates. Once a quantitative risk assessment has emerged, an analyst can then use a qualitative assessment to modify it for such factors as currency and industry risk, industry characteristics, and the firm's competitive position in that industry (Altman, 1977).

Table 2.4 Original and revised Altman's models

Original Altman's model		Revised Altman's model	
Coefficient	Ratio	Coefficient	Ratio
1.2	Working capital/total assets	0.717	Working capital/total assets
1.4	Retained earnings/ total assets	0.847	Retained earnings/ total assets
3.3	Operating profit (EBIT)/ total assets	3.107	Operating profit (EBIT)/ total assets
0.60	MVE/total liabilities	0.420	BVE/total liabilities
0.99	Sales revenues/total assets	0.998	Sales revenues/total assets
Original Z = 1.2X1 +1.4X2 +3.3X3 +0.60X4 +0.99X5		Revised Z = 0.717X1 +0.847X2 +3.107X3 +0.420X4 +0.998X5	

From the application of the Z"-score, Altman and Hotchkiss (2006) mapped a correspondence between the score and the ratings assigned by Standard & Poor's, as shown in **Table 2.5**. Altman and Narayanan (1997) gave their conclusion that accounting models based on financial ratios such as (logistic regression, MDA and probit models) play an active role in predicting failure risks.

Table 2.5 Correspondence Between Z''-score and S&P Rating

	Rating	Z'' Score		Rating	Z'' Score
SAFE ZONE	AAA	>8,15	GREY ZONE	BB+	5,65
	AA+	8,15		BB	5,25
	AA	7,60		BB-	4,95
	AA-	7,30		B+	4,75
	A+	7,00		B	4,50
	A	6,85	DISTRESS ZONE	B-	4,15
	A-	6,65		CCC+	3,75
	BBB+	6,40		CCC	3,20
	BBB	6,25		CCC-	2,50
	BBB-	5,83		D	<1,75

2.5 Ohlson's Logit Model

Ohlson (1980) believes the discriminant analysis generates a score which has little intuitive interpretation, since it is basically a mere ranking tool. In particular, he criticizes the following restrictive assumptions of MDA:

1. The first assumption is that the explanatory variables are normally distributed.
2. The second assumption is equal variance and covariance of the explanatory variables for the bankrupt and non-bankrupt firms (Ohlson, 1980).
3. Bankrupt and non-bankrupt firms are matched according to criteria such as size and industry, and these tend to be somewhat arbitrary. Ohlson (1980) claimed that variables should be included to predict bankruptcy not for matching purposes. This statement is outdated since recent studies use size and industry to make a matched-pair and therefore to control for these variables.

Therefore, Ohlson (1980) developed an alternative econometric technique based on logistic transformations (logit model) which eliminates those restrictive assumption and provides defined probabilities of failure as output of the function.

Ohlson (1980) identifies four factors that significantly affect the probability of bankruptcy. These are: 1) the size of the company; 2) a measure(s) of the financial structure; 3) a measure(s) of performance; 4) a measure(s) of the current liquidity.

In order to assess the impact of these four variables he uses a logit model which implies the use of 9 financial ratios:

- *X1: Log (Total assets/GNP price-level index)*
- *X2: Total Liabilities divided by Total Assets*
- *X3: Working Capital divided by Total Assets*
- *X4: Current Liabilities divided by Current Assets*
- *X5: 1 if Total Liabilities exceed Total Assets, 0 otherwise*
- *X6: Net Income divided by Total Assets*
- *X7: Funds provided by operations (income from operations after depreciation) divided by Total Liabilities*
- *X8: 1 if Net Income was negative for the last 2 years, 0 otherwise*
- *X9:* $(NI_t - NI_{t-1})$ *divided by* $(|NI_t| + |NI_{t-1}|)$

Where: NI_t is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income.

The logit model aims to estimate an accurate probability of failure to reduce the misclassification errors by using logistic cumulative distribution.

$P= (1+ e^{(-Z)}) = (1+ e^{-(W_0+W_1X_1+\ldots+W_nX_n)})$

Where:

- P= probability of bankruptcy
- Z= linear combination of the independent variables
- Wi= coefficient
- Xi= independent variables

This logit function maps the value of Z to a probability bounded between 0 and 1. If the company prospers it is the value 1 and if the company declared bankrupt it is the value 0.

In addition, Ohlson (1980) estimates three models using 105 bankrupt and 2058 non-bankrupt firms in the period between 1970 and 1976: Model 1 predicts bankruptcy within one year; Model 2 predicts bankruptcy within two years, given that the firm does not fail in the first year, and Model 3 predicts bankruptcy within one or two years. two years.

The overall O-Score function is defined as:

$$O\text{-Score} = -1.3 - 0.4X1 + 6.0X2 - 1.4X3 + 0.8X4 - 2.4X5 - 1.8X6 + 0.3X7 - 1.7X8 - 0.5X9$$

The higher the O-score, the higher the risk of bankruptcy.

Ohlson finds that a cut-off value of P= 0,038 minimizes the sum of type I and type II errors for his estimation sample. A type I error occurs if the O-Score is less than the cutoff point but the firm is bankrupt. If the O-Score is greater than the cutoff point but the firm is non-bankrupt, this is a Type II error. By the end of his study Ohlson concluded that the predictive power of the model depends upon when the financial report is made available, and the predictive powers seem to be robust across the estimation procedure.

Ohlson felt that his study had an important advantage related to the timing that allowed one to check whether the company entered bankruptcy prior to, or after the date of release for the financials. He claimed that previous studies did not explicitly consider the timing issue (Lawrence et al., 2015). Moreover, Ohlson (1980) believes that is model was simple to apply and it can be used in different circumstances. However, the logit model, brings a very modest improvement to the previous studies in terms of predictive accuracy (Paolone & Pozzoli 2017). Some authors (Keasey and Watson,1991) do not recognize the great advantage claimed by Ohlson and the model was criticized by Hensher et al., (2007) because “all parameters are fixed and the error structure is treated as white noise, with little behavioral definition”.

Hensher and Jones (2007) propose a mixed logit model instead of a simple logit model. This mixed logit model recognizes “the substantial amount of heterogeneity that can exist across and within all firms in terms of the role that attributes play in influencing an outcome domain” (Hensher and Jones, 2007, p. 243). Grice and Dugan (2003) indicated that the accuracy of the Ohlson’s model increased when the coefficients are re-estimated. This finding is the result of another research design proposed by Grice and Dugan (2003). Grice and Dugan (2003) evaluated the models with samples of distressed and non-distressed companies from time periods, industries, and financial conditions other than those used to develop the original models. One of the conclusions of Grice and Dugan (2003) is that the relation between financial ratios and bankruptcy appears to change over time.

2.6 Zmijewski's Probit Model

Zmijewski (1984) is the author of the probit analysis: an alternative technique which falls in the group of *multivariate conditional probability* models of failure prediction. Indeed, similarly to the logit analysis, the model of Zmijewski estimates the probability that the firm will go bankrupt. The only difference with the logit model is the requirement of a non-linear estimation (Dimitras et al., 1996)

Zmijewski (1984) finds out two recurrent estimation biases using bankruptcy prediction models: choice-based sample biases and sample selection biases. The choice-based bias is the result of "over-sampling" distressed firms (Zmijewski, 1984, p. 59). When bankrupt firms are chosen first, and then a match is chosen based on some criteria, the sample is not a random sample anymore (Paolone & Pozzoli, 2017). This led to biased probabilities in the models. The sample selection biases occur when "the probability of distress given complete data is significantly different from the probability of distress given incomplete data" (Zmijewski, 1984, p. 74).

The Zmijewski model (1984) based on the 40 bankrupt and 800 non-bankrupt firms is the most commonly used model by accounting researchers (Grice and Dugan 2003). He used the probit technique to construct his bankruptcy prediction model and found an accuracy rate for the estimation sample of 99%. He did not report the accuracy rate for the hold-out sample.

The population of firms consists of all firms listed on the American and New York Stock Exchanges during the period 1972 through 1978. Finance, service and public administration industries are excluded from the sample. He classifies firms as bankrupt if they filed a bankruptcy petition during this period and non-bankrupt if they did not. The final estimation sample contained 40 bankrupt and 800 non-bankrupt firms, and a hold-out sample containing 41 bankrupt and 800 non-bankrupt firms.

The constructed Probit function with the variables and estimated coefficients is the following:

$Zmijewski$ Score = $-4.3 - 4.5X1 + 5.7X2 + 0.004X3$

Where:

- $X1 = net\ income / total\ assets$
- $X2 = total\ liabilities /\ total\ assets$
- $X3 = current\ assets /\ current\ liabilities$

Grice and Dugan (2003) stated that one of the limitations of the study of Zmijewski (1984) is that the ratios were not selected on a theoretical basis, but rather on the basis of their performance in prior studies. The models of Altman (1968) and Ohlson (1980) have the same limitation. Furthermore, it is criticized because the original study used “financial ratios that discriminated among industrial firms” (Grice and Dugan, p. 85, 2003).

Like the logit function, the probit function maps the value between 0 and 1. However, Zmijewski (1984) classified the firms in a different way respect to Ohlson. Indeed, firms with probabilities greater than or equal to 0.5 were classified as bankrupt or having complete data. Firms with probabilities less than 0.5 were classified as non-bankrupt or having incomplete data.

Mehrani et al. (2005) applied Zmijewski´s probit model on firms listed at the Tehran Stock Exchange and shown that his model is able to divide firms into bankrupt and nonbankrupt firms. Further, Grice and Dugan (2001) applied Zmijewski model to 1988-1991 firms and reported an accuracy rate of 81.3 %. Although the accuracy rate of Zmijewski´s probit model seems to be high, there are some critics left.

Shumway (2001) doubted the predictive power of the probit model due to the high correlation between the variables. Platt and Platt (2002) argue that, although Zmijewski (1984) tried to avoid choice-based sample bias, his empirical test was weak. “Because he ran only one regression for each sample size, he could not test the individual estimated coefficients for bias against the population parameter, a more direct test of bias” (Platt & Platt, 2002, p. 186). By contrast, Platt and Platt (2002) used more standard tests of bias, comparing the mean estimated coefficient to the population parameter. The number of studies that used probit analysis compared to other methods was however relatively small, probably because the probit technique requires more computations (Dimitras et al. 1996; Gloubos & Grammatikos 1988).

Grice and Dugan (2001) investigate the generalizability of Zmijewski’s (1984) and Ohlson’s (1980) bankruptcy prediction models and they find out that the accuracy of the models declined when applied to alternative samples. The probit model was significantly more accurate than the logit model. Indeed, Ohlson’s model was very sensitive to industry classification. Finally, they conclude that both logit and probit analysis were more generally useful for identifying firms that were financially distressed, as opposed to the more limited condition of bankruptcy.

2.7 Other Models of Bankruptcy Prediction

The univariate analysis, the multivariate discriminant analysis and the logit and probit analysis may suffer from several drawbacks, such as multicollinearity, probability distribution and non-linear relationship (Paolone & Pozzoli, 2017).

Over the years, new models were discovered in order to overcome such limitations. The alternative techniques involve the use of Artificial Intelligence and they are not subject to the restrictive assumptions required for statistical methods (Sun et al., 2014). Some of the most popular artificial intelligence models are the Neural Networks, Support Vector Machine, Cased-based reasoning, Rough set and Decision tree.

2.7.1 Neural Networks

Artificial Neural Networks is a way to process information inspired by biology, which resulted to be effective in forecasting and classification decision problems.

Many applications of Neural Networks in business field were shown to be more successful than traditional regression analysis. Wilson and Sharda (1994) compared the performance of Neural Networks models with the discriminant analysis. They proved that NN outperformed discriminant analysis in prediction accuracy, especially in the prediction of bankrupt firms, the more difficult and, arguably, the more important classification problem. Zurada et al. (1998) Eftekhar et al. (2005) also find that the neural networks can better describe the complex relationships among variables than the logistic regression analysis can. Thus, this model should be used with non-linear complex interactions.

Although Neural Networks can overcome some limitation of statistical models, superior results over discriminant analysis and probabilistic models were not observed (Charitou et al. 2004; Coats and Fant 1993). Generally, Neural Networks models are perceived difficult to understand and structured in a complex way. They also require far more sample data compared to statistical models (Sun et al., 2014).

2.7.2 Support Vector Machine

Support Vector Machine is an alternative bankruptcy prediction model based on risk minimization (Wang et al., 2005). SVM transforms complex problems (with complex decision surfaces) into simpler problems that can use linear discriminant functions, and it has been successfully introduced in several financial applications recently (Min and Lee, 2005)

The linear model represents a non-linear decision in a high-dimensional space. In the space, an optimal separating hyperplane (OSH) is constructed. Thus, SVM is known as the algorithm that finds a special kind of linear model, the maximum margin hyperplane. The maximum margin hyperplane gives the maximum separation between decision classes. The training examples that are closest to the maximum margin hyperplane are called support vectors (Min and Lee, 2005)

Many authors (Shin et al., 2005; Min and Lee, 2005; Hui and Sun, 2006; Ding et al., 2008) adopted this model to assess the probability of bankruptcy and they reached the conclusion that the SVM model outperformed multiple discriminant analysis, logit model and neural networks in terms of prediction accuracy. By contrary, some others (Bose and Pal, 2006) do not reached the same result.

2.7.3 Case-based Reasoning

In business forecasting, managers often use the outcome of past analogous cases to predict the outcome of the current one (Jo, Han and Lee, 1997). They (1) observe significant attributes in describing a case, (2) identify past cases similar in these attributes to the current case, and (3) predict the outcome of the current case based on those of the analogous cases identified through some mental simulation and adjustment.

The basic principle of CBR is that similar problems have similar solutions (Sartori et al., 2016). The evident advantage of CBR is that it is easy to understand, and its prediction accuracy is also relatively high with the development of CBR technique.

By comparing CBR, NN and MDA, Jo, Han and Lee (1997) found that there was no real difference between CBR and MDA, and CBR performed well when data was not sufficient.

2.7.4 Rough Set

Rough set theory was developed in the 1980s by Z. Pawlak (1982, 1984, 1991), and Pawlak et al. (1995) among others, to deal with the problem of indiscernibility between objects in a set.

The aim of rough sets theory is to classify objects using imprecise information. In a rough sets model, knowledge about the objects is presented in an information table that, in effect, works like a decision table containing sets of condition and decision attributes that is used to derive the decision rules of the model by inductive learning principles. Every new object (for example, a firm) can then be classified (healthy or in financial distress) by matching their characteristics with the set of derived rules (Aziz and Dar, 2006).

Some years later, the rough set approach has been proposed for evaluation of bankruptcy risk (Slowinski and Zopounidis, 1995). The greatest advantages of these models based on rough set approach compared to statistical models are: 1) the relatively simplicity of interpretation (Roy, 1993); 2) the use of original data without requiring any additional information, such as probability distributions in statistics (Pawlak, 1991); 3) the combination of quantitative and qualitative variables. However, it has been shown that rough set models have the shortcomings of unfixed structure and poor universality (Sun et al., 2014).

2.7.5 Decision Trees

Decision tree induction approaches construct a decision tree using a training data set, where the tree is a simple recursive structure for representing a decision procedure in which a new case is assigned to one of the predefined classes. A nonterminal (interior) node in the tree represents a decision attribute value test, and a terminal (leaf) node denotes a decision class (Sung et al., 1999).

Inductive learning is a technology that automatically extracts knowledge from training samples, in which dedicated algorithms such as ID3 (Quinlan, 1986) and classification and regression trees (CART) generate a tree type structure to organize cases in memory. Thus, the difference between a statistical approach and an inductive learning approach is that different assumptions and algorithms are used to generate knowledge structures.

Messier and Hansen (1988) extracted bankruptcy rules using rule induction algorithm that classifies objects into specific groups based on observed characteristics ratios. They drew their data from two prior studies and began with 18 ratios. Their algorithm developed a bankruptcy prediction rule that employed five of these ratios. This method was able to correctly classify 87.5% of the holdout data set.

Shaw and Gentry (1990) applied inductive learning methods to risk classification applications and found that inductive approach performed better than probit or logit analysis. They have concluded that this result can be attributed to the fact that inductive learning is free from parametric and structural assumptions that characterize statistical methods

Table 2.6 Review of the Main of Bankruptcy Prediction Model

	Beaver (1966)	Altman (1968)	Ohlson (1980)	Zmijewski (1984)
Statistical Technique	Univariate	Multivariate (MDA)	Logit regression	Probit regression
Sample size	79 bankrupts	N= 66 33 bankrupts 33 non-bankrupts	N= 2163 105 bankrupts 2058 non-bankrupts	N= 840 40 bankrupts 800 non-bankrupts
Independent variables of profitability	15 of net income ratios (4) Turnover ratios (11)	EBIT/TA SALES/TA	Net Income/TA Change in Net Income	Net Income/TA
Independent variables of liquidity	11 of cash flow ratios (4), Liquid-Assets to Tot. Assets ratio (4), Liquid-Asset to Current Debt Ratio (3)	Working Capital/TA	Working Capital/TA CL/CA Funds/ TL INTWO	CA/CL
Independent variables of leverage	4 of Debt divided by TA	Retained Earnings/TA MV of Equity/BV of Debt	TL/TA OENEG	Total Debt/TA
Other independent variables			Size= Log (TA/GNP price-level index)	

Source: Paolone & Pozzoli, 2017

TA Total assets, EBIT before interests and taxes, MV market value, BV book value, CA current assets, CL current liabilities, Funds ¼ Funds provided by operations, OENEG ¼ variable that takes value of 1 if Total Liabilities > Total Assets, 0 otherwise; INTWO ¼ dummy variable that takes value of 1 if Net Income was negative in the last 2 years, 0 otherwise.

Different scholars have used different criteria to create their models of bankruptcy prediction, however after a detailed and comprehensive analysis of the previously studies and other related researches, 13 criteria have been recognized as the most common and significant.

Example of other reviewed studies include Tam and Kiang, (1992); Haykin, (1994); Zurada et al., (1994); Edum-Fotwe et al., (1996); Dreiseitl and Ohno-Machado, (2002); Min and Lee, (2005); Shin et al., (2005); Balcaen and Ooghe, (2006); Ravi Kumar and Ravi, (2007); Chung et al., (2008); Ahn and Kim, (2009); to mention a few. The identified 13 criteria are the followings:

1) Accuracy: This refers to the percentage of firms a model correctly classifies as failing or non-failing.
2) Result transparency: This relates to the interpretability of a tool's result.
3) Non-deterministic: The case where a tool is not able to effectively classify a firm
4) Sample size: This refers to the sample size(s) suitable for an optimal performance of the tool.
5) Data dispersion: This refers to ability of a tool to handle equally or unequally dispersed data
6) Variable selection: This relates to the variable selection techniques needed for optimum tool performance.
7) Multicollinearity: This refers to sensitivity of a tool to collinear variables.
8) Variable types: The ability of a tool to analyze quantitative and/or qualitative variables.
9) Variable relationship: This explains a tool's limitation in analyzing linear or non-linear variables
10) Assumptions imposed by tools: Requirements a sample data must satisfy for a tool to perform optimally.
11) Sample specificity/overfitting: This is when the model developed from a tool performs well on sample companies but poorly on validation data.
12) Updatability: The ease with which a tool's model can be updated with new sample firms and its effectiveness afterwards
13) Integration capability: the ease with which a tool can be hybridize.

2.8 The Role of Cash Flow-Based Ratios in Predicting Corporate Failure

Cash flow is a critical indicator of corporate solvency. Heath (1978) relates cash flow to financial flexibility when he states that financial flexibility is the firm's ability "to control cash receipts and payments to survive a period of economic adversity." Further, Heath and Rosenfield (1979, p.48) argued that:

Solvency is a money or cash phenomenon. A solvent company is one with enough cash to pay its obligations; an insolvent company is one with inadequate cash. Evaluating solvency is basically a problem of assessing the risk that a company will not be able to raise enough money before its debts must be paid.

Although the newly methods of bankruptcy prediction involving artificial intelligence clearly provide some benefits, they are more complex to implement, and they require more specialized tools. As a matter of fact, accounting-based models resulted to be easier to implement and to interpret (Paolone & Pozzoli, 2017). For this reason, accounting-based models are still widely used in bankruptcy prediction studies.

This paper takes inspiration from the empirical work of Paolone and Pozzoli (2017), who applied the Altman's Z-score model to a list of Italian manufacturing firms, precisely 9302 active companies vs. 783 failed during the period 2007–2015. In particular, the first version of Altman's model (the original one) was found to be 41.89% accurate in predicting bankruptcy, however the model is not significant at a level of 46.10% since 361 out of 783 Failed companies are classified as "not at risk". Regarding the active companies, the original Altman's model (1968) has a very low predictive power: it is accurate at 22.39% while it is only considered significant at 36.13%. The second version of Altman's model (the revised one) is accurate at 39.21% in estimating bankruptcy but it is only considered significant at 37.80% since 296 out of 783 Failed companies are classified as "not at risk". Regarding the Active companies, the model is accurate at a mere 14.16% while it is not significant at 23.11%.

Furthermore, a large percentage of Active companies are included in the grey area (62.73%). The second-version model has a lower predictive power than the original model. Both models have a weak ability to predict bankruptcy.

The result of the study (Paolone & Pozzoli, 2017) has shown the limited predictive ability of the accrual accounting-based ratios taken from the balance sheet and income statement, also defined as "static" ratios. That is, the conventional accrual ratios that have been used by most of the academics is not so adequate for bankruptcy forecasting within the Italian scenario.

Among the intense literature over failure prediction, very few studies have considered the ratios taken from the Cash Flow statement (Bhandari and Iyer, 2013). As a matter of fact, many scholars (e.g. Zavgren, 1983; Jones, 1987; Neill et al. 1991; Watson, 1996) shared the opinion that data taken from cash flow statement does not contain significant incremental information content over accrual information in discriminating between bankrupt and non-bankrupt firm. However, the relationship between cash flow and bankruptcy seems to be logic for some others (Sharma, 2001).

Cash flow statement includes all the cash inflows and outflows from three main areas: Operating, Investing and Financing. Among these three macro areas, cash flows from the operating activities is recognized to be the most reasonable and useful source of information for corporate financial distress investigation. Cash flow from Operation is a clearly defined number, meticulously calculated and universally disclosed as a part of cash flow statement (Bhandari and Iyer, 2013).

Beaver (1966) in his study, was the first who recognized the lower probability of error for the cash flow ratio, (defined as cash flow from operations (CFFO), proxied by net income plus depreciation, depletion and amortization, to total debt) relative to the other accrual-based ratios. Largay and Stickney (1980) recognized the limitation of defining CFFO as net income plus depreciation, depletion and amortization, and they realized that one had to adjust for changes in current assets and current liabilities other than cash, in order to determine the cash flow.

Sharma (2001), reviews all the studies investigating the ability of cash flow information to predict corporate failure and he shows the mixed results. Gilbert et al. (1990) observed that contrary to the findings of Casey and Bartczak (1985), cash flow ratios were significant predictors of distress. In particular, the most powerful ratios were cash flow from operations to total liabilities (CFFO/TL) and cash flow from operations to current liabilities (CFFO/CL).

The importance of cash flow ratios was proven by Rujoub et al. (1995). They found that (a) cash flow data predict bankruptcy better than accrual accounting data, and (b) the use of cash flow data in conjunction with accrual accounting data improves the overall predictive power of accrual accounting data used in previous studies for predicting business failure. The rationale behind this result is that the inability of a corporation to generate cash from its operations over time may force the firm to borrow more money or to dispose of its capital investments to meet its obligations. If this situation persists over an extended period of time, it may lead to an involuntary bankruptcy (Rujoub et al., 1995).

According to Luo (2008), cash flow from operations provide a key metric in assessing a firm's ability to generate cash from its internal operations and to remain viable.

Bhandari and Iyer (2013) underline that cash is what buys things, pays wages and salaries; services and pays debt; and compensates stockholders. Additionally, cash generation is highly correlated with profit generation. Therefore, information over cash should be much more considered than those on accounting income. To reach this conclusion, Bhandari and Iyer (2013) analyzed a sample of 50 failed firms from the period 2008-2010, belonging to 20 different industries, and they used seven-predictor variables, six of which were cash flow based. The model correctly classified 83.3 percent of the firms.

Moreover, the relative value relevance of cash flows versus accrual accounting information items is enhanced by Aharony et al. in 2006. In their comparative study, they find out that cash flow ratios predict better in the growth period of a firm and also that cash flow information more accurately reflect the firm's market value.

The importance of cash flow components was finally recognized in 2015, with the Legislative Decree 139, which imposed to all Italian companies, with the exception for micro firms and firms that deliberate statement in abbreviate form, the cash flow statement as part of the mandatory disclosure, together with the balance sheet and the income statement.

Summarizing the previously mentioned studies, the most relevant accounting ratios taken from the cash flow statement of an enterprise for the purpose of corporate financial distress prediction, resulted to be:

1. *Operating Cash Flow return on Total Asset* (Cash Flow from Operation/Total Assets):
2. *Operating Cash Flow to Debt* (Cash Flow from Operation/Total Liabilities):
3. *Operating Cash Flow Margin* (Cash Flow from Operation/Sales):

Considering this flow of literature, the present work wants to test the Altman's Z-score model for a sample of Italian firms belonging to the Financial service Industry. Moreover, I am going to introduce these three new ratios from the Cash Flow statement in addition to the traditional Altman's ratios.

The aim of the study is to update the traditional Altman's Z-score model by adding more powerful predictor ratios taken from the cash flow statement and to prove their contribution to enhance the predictability of corporate bankruptcy using a multivariate model.

CHAPTER III

Empirical Analysis

In this chapter, I am going to test the Altman’s Z-score model for a sample of Italian financial companies. As a starting point, I will consider the previous findings by Paolone and Pozzoli (2017). They applied both versions of the Altman’s Z-score model, named the revised and the original one and they proved that the accounting ratios used by Altman in his model are not significant for bankruptcy prediction when considering Italian manufacturing companies.

Therefore, I propose to include in the Altman’s model, three new ratios taken from the cash flow statement, together with the five traditional ratios taken from the accrual accounting-based financial statements. Moreover, I decided to analyze one of the least considered industry for this type of argument, the financial Industry.

After the illustration of the sample data and the variables considered in the proposed model, the present chapter explain how I developed the analysis, step by step. More precisely, I developed two different assessment, based on non-parametric statistical test, one with the outliers and one without outliers, since the result resulted to be highly influenced by these.

The purpose of this empirical analysis is to prove the importance of cash flow information together with accrual accounting-based data for bankruptcy prediction. Nevertheless, it is important to build a model suitable for the Italian context that is able to improve the bankruptcy predictive power of the existing model.

3.1 Sample Data

The companies object of this empirical study are all Italian firms and they belong to the Financial industry stratified by subindustries. The financial subindustries include all type of financial services activities, insurance, reinsurance and pension funding, real estate activities, legal and accounting activities and other activities auxiliary to the previous ones.

I decided to focus my empirical analysis on the financial service industry for some reasons. First of all, because of the scarcity of related studies concerning bankruptcy prediction, comparing to the industrial and manufacturing sector. Therefore, I decided to develop the work also with the aim of understanding which are the limitations and assumptions that must be considered when dealing with this particular sector. Finally, because of personal interest.

The sample companies are all Public Limited Companies by Shares (Società per Azioni or S.p.A.). Moreover, the selected firms are not listed on any stock exchange.

After the initial groups are defined and firms selected, balance sheet and income statement data are collected using AIDA, the financial dataset of Bureau van Dijk (BvD) for the Italian companies.

The sample is then divided in two groups: Group 1 consists of 4952 active companies while group 2 consists of 2623 bankrupted firms filed under bankruptcy petition in the period 2016 - 2017. The mean assets size for the Italian Active firms is 561.930€ and 391.719€ on average for Failed companies.

The firms were not matched on size, nor was size included as an independent variable, even though it has been found to be a significant discriminator in previous bankruptcy research (Casey & Bartczak, 1985). However, the discriminatory power of size was not an issue of interest in the present study.

Through the financial statements of the companies, data are collected in order to complete the eight financial ratios used in the model.

3.2 Variable Selection

As we just said, the model in this chapter is based on eight financial ratios. The first five ratios are the traditional ones, the accrual accounting-based ratios taken from the income statement, applied by the Altman's model. In addition to these five traditional ratios, we further include three new ratios taken from the cash flow statement.

The five traditional ratios belong respectively to five group categories:

1. X1 (Working Capital/ Total Asset) – Liquidity Ratio:
   Liquidity is the degree to which an asset or security can be quickly bought or sold in the market without affecting the price of the asset (P&P). Liquid assets such as cash and marketable securities constitute a considerable portion of total assets (John, 1993). Moreover, liquidity is needed to meet current obligations and to face financial constraints. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets. Therefore, liquidity is strictly related to financial distress when shortage of liquidity occurs, and it must be included in the bankruptcy prediction model. Among the liquidity ratios, Altman (1968) selected the Working Capital to Total Assets as a measure of liquidity situation since it is considered the most valuable one (Altman, 1977).
2. X2 (Retained Earnings/ Total Asset) – Profitability Ratio:
   Profitability is the ability to generate profit. Profit is derived by subtracting all the related costs and expenses from the income earned. Profitability measures are essential for assessing the firm's soundness. Among the ratios from this class, Retained Earning to Total Assets is the preferred one in terms of predictive power.
3. X3 (EBIT/ Total Assets) - Operating efficiency Ratio:
   Operational efficiency measures the efficiency of profit earned as a function of operational costs. A market is defined as operationally efficient when conditions exist allowing players to perform transactions and receive services at a price that equates fairly to the actual costs required to provide them. Operating measures generally consider the output over the input. In the model, the ratio used to measure the true productivity is Operating Profit (EBIT) to Total Assets.
4. X4 (Book Value of Equity/ Total Liabilities) – Leverage Ratio:
   The leverage measures the degree to which companies use to finance their capital and operations with debt (loans). The measure is expressed as the Book Value of Equity divided by the total financial debt. The just mentioned ratio is an indicator of the

company’s ability to meet its obligations, therefore it is clearly fundamental for our purpose.

5. X5 (Sales/ Total Assets) - Competition/Asset Turnover Ratio:
   The competitivity of a company or its asset turnover, is basically the degree to which the company is able to use its assets to generate sales. Nevertheless, the asset turnover ratio is an indicator of the company’s efficiency in using assets to generate profit. The related measure used in the model is the ratio between Total Sales Revenue and Total Assets.

However, the news of this work are the Cash Flow variables. The ones used for the analysis were selected considering their popularity in the literature. In particular, the ratios used are the following: (Bhandari)

1. X6 (Operating Cash Flow/ Total Assets): This ratio is similar to the traditional Return on Asset (ROA) and it measures the ability of the firm’s assets to generate cash (Bhandari and Iyer, 2013).
2. X7 (Operating Cash Flow/ Total Liabilities): This ratio measures the firm’s ability to repay the debt using cash generation. Therefore, the lower the ratio the higher the probability of default. We will use this cash ratio as a key to solvency (Sharma, 2001).
3. X8 (Operating Cash Flow/ Sales): This ratio is similar to the accrual profit margin and it measures the firm’s ability to translate sales into cash. According to Bhandari and Iyer (2013) it is a more reliable measure of the firm’s operating profitability

3.3 Research Methodology

After collecting the financial data through AIDA database, I computed the eight ratios described in the previous paragraph, both for the active and inactive group of firms, using separate excel spreadsheets.

By doing this, I noticed that some values were not available for all the companies. As a matter of fact, the sample companies are not listed on any stock exchange, and thus, the available information are limited.

This is the first limitation of the model that makes the sample smaller, since I removed the companies for which the information needed were not completely available. In particular, the sample of inactive firms shrink to 1,092.

Then, in a unified excel spreadsheet I inserted all the computed ratios for both the situations of financial soundness, and I differentiated them by coding “1” for failed firms and “0” for active companies. **Image 3.1** and **image 3.2** present a portion of the excel spreadsheet of the

final dataset, respectively one for the first 50 active companies and one for the first 50 failed companies.
Afterwards, computed data were analyzed by using STATA software for statistics.

In order to complete the investigation, I utilized non-parametric statistical tests by doing two different analyzes: for the first analysis, I took all the data from the original dataset.
Since we have two cases, noted as “failed” and “non-failed” our goal is to understand if the variables, which are, the above-mentioned ratios, contribute in the determination of the different status, and which of the variables contributes the most. Therefore, the significance level is particularly important for our study because it tells us that what is observed is hardly due to chance.
The significance level in a statistical test is given by the P-value and it is used in order to determine the relative contribution of each independent variables.
A variable is significant when the P-value is below 0,1% because generally, the ratio 1/100 (i.e.) is small enough to conclude that it is "unlikely" that the observed difference is due to the simple case.
The result of the first trial shows that the variables we are interested in, that are, the cash flow ratios, are not significant for the model, meaning that they are not useful for bankruptcy prediction because they do not contribute to the assessment of a company’s financial soundness.
As we can see from the **image 3.3**, the only variable that is significant for the model is X4 (Book Value of Equity divided by Total Liabilities), and overall, we can say that this model has a weak ability to predict bankruptcy risk. Indeed, only one of eight variables resulted to have a discriminant power. This result is not in line with the one of Altman in each of his works.

Image 3.1 Excel Spreadsheet of the final dataset related to "active" companies (Example first 50)

	Y	X1	X2	X3	X4	X5	X6	X7	X8
	FAILED (1) / NO FAILED (0)	WC/TA	RE/TA	EBIT/TA	BVE/TL	S/TA	CFO/TA	CFO/TL	CFO/S
'ALBA CHIARA SOCIETA' PER AZIONI''	0,0000	0,7221	0,1871	0,0009	-0,3294	0,0277	-0,0747	-1,5217	-2,6951
'DOMUS MARIAE SOCIETA' PER AZIONI''	0,0000	0,4579	0,0444	-0,0147	-0,3188	0,1003	0,1332	0,6399	1,3287
'SOCIETA' DI COORDINAMENTO SOCIETA' PER A	0,0000	0,4001	0,1708	0,0611	-0,2572	0,1466	0,4772	3,1093	3,2558
'SOGIMI SOCIETA' PER AZIONI''	0,0000	0,1871	0,0509	0,1370	-0,0654	0,1093	0,1169	2,7626	1,0690
+NAVALMAR S.P.A.	0,0000	0,1972	0,7663	0,0128	-0,0158	0,0000	0,0000	0,0000	0,0000
035 INVESTIMENTI S.P.A.	0,0000	0,2085	-0,0869	-0,0263	-0,0215	0,0047	0,0146	0,6927	3,0982
21 INVESTIMENTI SOCIETA' DI GESTIONE DEL RI	0,0000	0,0000	0,0000	1,1042	0,0000	1,1042	0,0000	0,0000	0,0000
24 FINANCE MEDIAZIONE CREDITIZIA S.P.A.	0,0000	0,0739	-0,0109	0,0276	-8,0045	3,1493	0,1129	0,1367	0,0359
2I AEROPORTI S.P.A.	0,0000	-0,0259	0,0000	0,0504	-0,5881	0,2022	0,0524	0,1786	0,2593
2I TOWERS HOLDING S.P.A.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
2I TOWERS S.P.A.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
3 CIME S.P.A.	0,0000	0,0143	0,0000	0,1569	-0,0289	0,0000	0,1372	4,8821	0,0000
33 S.P.A.	0,0000	-0,0425	0,0000	0,0388	-2,7211	0,1343	0,1994	0,3202	1,4843
3P S.P.A.	0,0000	0,0426	0,0000	0,0061	-0,0196	0,0567	0,0193	1,0546	0,3411
3V PARTECIPAZIONI INDUSTRIALI S.P.A.	0,0000	-0,0068	0,0679	-0,0057	-2,7081	0,7843	0,1393	0,2007	0,1776
3V S.P.A.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
4 PARTNERS S.P.A.	0,0000	0,1768	0,0000	0,0472	-0,4742	0,0215	0,0000	0,0000	0,0000
4G HOLDING S.P.A.	0,0000	-0,1348	0,0000	-0,1019	-4,1545	1,9711	0,0000	0,0000	0,0000
4S HOLDING S.P.A.	0,0000	0,0986	0,2124	0,0272	-0,1060	0,0000	0,0379	0,3982	0,0000
5 ERRE S.P.A.	0,0000	0,1742	0,0557	0,0178	-3,2350	1,8484	0,0000	0,0000	0,0000
520 S.P.A.	0,0000	0,1209	0,0000	0,0606	-1,5014	2,1248	0,0000	0,0000	0,0000
55.11 S.P.A.	0,0000	0,1207	0,0000	-0,0201	-7,2884	0,0000	0,0000	0,0000	0,0000
6B INVESTIMENTI S.P.A.	0,0000	-0,0258	0,0000	0,0481	-0,5148	0,1568	0,0503	0,1496	0,3205
6SICURO S.P.A.	0,0000	-0,3717	-0,0024	-0,5511	5,5532	1,1558	-0,7145	-0,6147	-0,6182
81 SOCIETA' DI CONSULENZA FINANZIARIA FAM	0,0000	0,8321	0,0000	0,0896	-0,1349	0,7114	0,0248	0,2226	0,0349
A & P CONSULTING S.P.A.	0,0000	0,4515	-0,0980	-0,0251	-0,2859	0,1904	0,0209	0,1089	0,1097
A & P PARTNERS SPA	0,0000	-0,2136	0,0000	0,0070	-0,5151	0,0302	-0,0129	-0,0380	-0,4265
A&G REAL ESTATE SOCIETA' PER AZIONI , IN BRE	0,0000	0,5511	-0,0078	0,0041	-0,6498	0,0714	0,0000	0,0000	0,0000
A-LEASING SPA	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
A.C.M. SERVIZI ASSICURATIVI SPA	0,0000	0,4673	0,0000	0,0022	-1,1400	1,1129	0,0094	0,0209	0,0084
A.CO.IN. - S.P.A.	0,0000	0,5420	0,0000	0,0050	-1,9140	0,0775	0,1787	0,2790	2,3068
A.D. GROUP S.P.A.	0,0000	-0,0783	-0,1200	0,0493	-4,8253	1,5395	0,1378	0,1789	0,0895
A.D. PUGLIESE S.P.A.	0,0000	0,4337	0,0000	0,0446	-1,4938	3,0695	0,0000	0,0000	0,0000
A.F.I.S. IMMOBILIARE S.P.A.	0,0000	-0,0773	0,0000	0,0396	-0,2516	0,1081	0,0719	0,3579	0,6656
A.G.LA.R. S.P.A.	0,0000	0,8824	-0,0434	-0,0657	-52,6547	0,0024	-0,0718	-0,0782	-30,2655
A.I.S.A. S.P.A. AREZZO IMPIANTI E SERVIZI AMBI	0,0000	0,4764	0,0007	0,0035	-0,7808	0,0000	-0,0824	-0,1919	0,0000
A.M.U. INVESTMENTS - SOCIETA' DI INTERMEDI	0,0000	0,0000	0,0000	0,0416	0,0000	0,0416	0,0000	0,0000	0,0000
A.R.G.O. - S.P.A.	0,0000	0,2808	-0,0515	0,0463	-1,5987	1,0247	0,0446	0,0767	0,0435
A.S.D.E.A. S.A.P.A. DI GIULIANO AMBROSINI E F	0,0000	-0,2036	0,0000	0,1393	-0,5966	0,0000	0,0566	0,1516	0,0000
A.T.I. - S.P.A.	0,0000	0,9923	-0,3130	-0,0176	-0,0942	0,0000	0,0837	3,0676	0,0000
A1 LIFE S.P.A.	0,0000	0,2556	0,0507	0,0895	-4,4077	1,3362	0,0962	0,1449	0,0720
A3 AGENTI ASSICURATIVI ASSOCIATI S.P.A. IN F(	0,0000	0,2365	0,0000	0,2419	-1,5949	0,8028	0,3960	0,7601	0,4932
AB2H S.P.A.	0,0000	0,0542	-0,0643	-0,3262	-8,7417	0,0000	0,0000	0,0000	0,0000
ABA SOCIETA' PER AZIONI	0,0000	0,0280	-0,0204	-0,0069	-0,0076	0,0000	-0,0137	-1,8148	0,0000
ABACO IMMOBILIARE S.P.A.	0,0000	0,5856	0,0000	0,1781	-0,0613	0,0201	0,3277	285,4048	16,3237
ABC ASSEVERA S.P.A.	0,0000	-0,2029	0,0000	0,1614	-1,6686	0,2416	0,0000	0,0000	0,0000
ABC ASSICURA SOCIETA' PER AZIONI BREVEMEN	0,0000	0,0000	0,0000	0,2835	-3,0755	0,2835	0,0000	0,0000	0,0000

Image 3.2 Excel Spreadsheet of the final dataset related to "Failed" companies (Example first 50)

ALCA - S.P.A. IN LIQUIDAZIONE	1,0000	0,7126	-0,3737	-0,0520	24,5393	0,0000	-0,1039	-2,6681	0,0000
ALEF 4 S.P.A.	1,0000	-0,0017	-0,0076	-0,0116	421,9289	0,0000	-0,0553	-23,3702	0,0000
ALETTI GESTIELLE SOCIETA' DI GESTIONE DEL RI	1,0000	0,0000	0,0000	1,6082	0,0000	1,6082	0,0000	0,0000	0,0000
ALSER S.P.A.	1,0000	-0,1690	-0,0893	-0,0237	0,3430	0,0813	-0,0482	-0,0648	-0,5932
AMEDEO DELLA VALENTINA S.P.A. IN LIQUIDAZI	1,0000	-7,2684	-9,5633	-0,3399	-0,9041	0,0000	0,1232	0,0149	0,0000
ARCHIMEDE 1 S.P.A.	1,0000	0,1914	-0,1201	0,0128	4,9333	0,0000	0,3028	1,7969	0,0000
ARIETE S.P.A. IN LIQUIDAZIONE	1,0000	1,0000	0,0000	-0,4524	0,0000	0,1819	1,4045	0,0000	7,7196
ATMOS VENTURE S.P.A. IN LIQUIDAZIONE	1,0000	0,6909	-0,1233	-0,0185	2,2353	0,0000	-0,0369	-0,1195	0,0000
ATTIFIN S.P.A. IN LIQUIDAZIONE	1,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
AURORA S.P.A. IN LIQUIDAZIONE	1,0000	0,9967	0,0299	-0,9740	303,5339	0,0000	-0,0600	-18,2655	0,0000
AURUM ET PURPURA S.P.A. SIGLABILE A E P S.P.	1,0000	0,4800	-1,7022	0,3954	10,9302	0,0000	0,3727	5,0304	0,0000
AUTOPORTO DI VENTIMIGLIA S.P.A.	1,0000	0,2696	-0,2253	0,0040	3,5047	0,1867	0,0168	0,0757	0,0900
AVM DEVELOPMENT S.P.A. IN LIQUIDAZIONE	1,0000	-0,0798	-0,2128	-0,2969	5,4166	0,0000	-0,4742	-3,1210	0,0000
BALTICA S.P.A. IN LIQUIDAZIONE	1,0000	-0,0066	0,1725	0,0062	23,6736	0,0000	0,0074	0,1829	0,0000
BANCA CARIM - CASSA DI RISPARMIO DI RIMINI	1,0000	0,0000	0,0000	-0,0120	0,0000	-0,0120	0,0000	0,0000	0,0000
BANCA FARNESE S.P.A. - IN LIQUIDAZIONE	1,0000	0,0000	0,0000	-0,0001	0,0000	-0,0001	0,0000	0,0000	0,0000
BANCA FINANZIARIA INTERNAZIONALE S.P.A. BF	1,0000	0,0000	0,0000	0,0996	0,0000	0,0996	0,0000	0,0000	0,0000
BANCA NUOVA S.P.A.	1,0000	0,0000	0,0000	0,0211	0,0000	0,0211	0,0000	0,0000	0,0000
BANCO DI NAPOLI S.P.A.	1,0000	0,0000	0,0000	0,0349	0,0000	0,0349	0,0000	0,0000	0,0000
BDB REAL ESTATE S.P.A. IN LIQUIDAZIONE	1,0000	-11,3865	-173,5521	-0,1561	-0,9193	0,0000	57,5685	4,6477	0,0000
BDF HOLDING S.P.A.	1,0000	-0,0389	0,0000	0,0376	2,3574	0,0604	0,0940	0,3201	1,5546
BI ELLE HOLDING S.P.A.	1,0000	0,2547	0,3377	0,0354	0,7289	2,6614	0,0419	0,0742	0,0157
BIDICI SPA	1,0000	-0,2198	0,0000	-0,0022	1,5724	0,0296	0,0212	0,0546	0,7160
BIOS S.P.A. IN LIQUIDAZIONE	1,0000	0,9934	-0,1440	0,3114	149,5959	0,0000	1,8968	286,4262	0,0000
BNP PARIBAS INVESTMENT PARTNERS SOCIETA'	1,0000	0,0000	0,0000	1,8507	0,0000	1,8507	0,0000	0,0000	0,0000
BOLOGNA IMMOBILIARE - SOCIETA PER AZIONI	1,0000	-0,0049	-0,4372	-0,0256	2,0234	0,0000	-0,0325	-0,0981	0,0000
BORMIOLI PHARMA BIDCO S.P.A.	1,0000	0,0943	0,0022	-0,0388	0,2827	0,0209	0,0000	0,0000	0,0000
BST SOCIETA' PER AZIONI IN LIQUIDAZIONE	1,0000	0,8369	-2,9138	-0,2225	4,5575	0,0000	-0,4450	-3,1307	0,0000
C&A - CONSULENTI ASSOCIATI S.P.A. IN LIQUID/	1,0000	0,0000	0,0000	0,4222	0,0000	0,4222	0,0000	0,0000	0,0000
C.I.S.E.M. COMPAGNIA INDUSTRIALE SICILIANA	1,0000	0,9718	0,0427	0,0119	1,1557	0,1573	0,0026	0,0062	0,0168
CAFIN S.P.A.	1,0000	-0,1309	0,0000	0,0708	0,8347	0,0178	-0,0794	-0,1459	-4,4643
CALA BLU S.P.A. - IN LIQUIDAZIONE	1,0000	-0,2686	-0,7369	-0,0034	-0,0078	0,0000	-0,0069	-0,0068	0,0000
CAPITOLO-OTTO S.P.A., IN LIQUIDAZIONE	1,0000	0,7537	187,7888	-0,0157	3,0596	0,0000	-0,0315	-0,1278	0,0000
CAPITOLOQUATTORDICI S.P.A.	1,0000	0,0413	0,0692	0,0503	0,9642	0,9431	-0,0043	-0,0085	-0,0045
CAPITOLOQUINDICI S.P.A. IN LIQUIDAZIONE	1,0000	0,3513	0,1346	0,1320	2,2418	0,6281	0,1454	0,4894	0,2315
CAPITOLOUNDICI S.P.A. IN LIQUIDAZIONE	1,0000	0,8364	2,9565	62,1547	5,1137	0,0000	61,0507	373,2474	0,0000
CAPRI S.P.A. IN LIQUIDAZIONE	1,0000	-0,3683	-0,4703	-0,1068	0,5968	0,0522	-0,4284	-0,6842	-8,2010
CARAPELLI FINANZIARIA - SOCIETA' PER AZIONI	1,0000	0,0677	-0,9417	-0,0013	14,4529	0,0000	0,0208	0,3311	0,0000
CARGOBULL FINANCE S.P.A. IN LIQUIDAZIONE	1,0000	0,9652	-0,3079	0,0017	25,7059	0,0100	-0,0065	-0,1865	-0,6432
CARIFIN ITALIA S.P.A. IN LIQUIDAZIONE	1,0000	0,7200	-2,4084	-0,2622	-0,8159	0,0081	-0,3697	-0,1449	-45,6521
CARISMA SOCIETA' DI GESTIONE DEL RISPARMI(	1,0000	0,0000	0,0000	0,2368	0,0000	0,2368	0,0000	0,0000	0,0000
CARTOFINANZIARIA - S.P.A.	1,0000	0,2048	0,0000	0,0136	67,2794	0,0220	-0,0104	-0,8158	-0,4728
CASA DI CURA SANTA CHIARA SOC. PER AZIONI	1,0000	0,7190	0,0000	-0,0008	2,5585	0,0000	-0,0016	-0,0056	0,0000
CASSA DEI RISPARMI DI FORLI E DELLA ROMAGI	1,0000	0,0000	0,0000	0,0258	0,0000	0,0258	0,0000	0,0000	0,0000
CASSA DI RISPARMIO DEL FRIULI VENEZIA GIULI	1,0000	0,0000	0,0000	0,0278	0,0000	0,0278	0,0000	0,0000	0,0000
CASSA DI RISPARMIO DEL VENETO S.P.A.	1,0000	0,0000	0,0000	0,0313	0,0000	0,0313	0,0000	0,0000	0,0000
CASSA DI RISPARMIO DI PISTOIA E DELLA LUCCH	1,0000	0,0000	0,0000	0,0341	0,0000	0,0341	0,0000	0,0000	0,0000
CASTEL FUSANO PRIMA SOCIETA PER AZIONI - II	1,0000	-0,1271	-0,1609	-0,0097	5,3529	0,0000	-0,0091	-0,0580	0,0000
CENTRO ITTICO CAMPANO S.P.A. IN LIQUIDAZIC	1,0000	0,2358	-0,3606	0,0080	-1,5428	0,2267	0,0260	0,1318	0,1147
CERAMICA MANDRIO CORREGGIO C.M.C. S.P.A	1,0000	0,3394	0,0000	0,0698	0,9295	1,0314	0,1230	0,2518	0,1192

Image 3.3 Statistical Result of the First Test

```
   wilcoxon_test          p_w kruskal_test          p_k
X1       2999938  1.638519e-08     31.88183  1.638428e-08
X2       2706268           NaN          NaN           NaN
X3       3034806  2.617947e-10     39.94079  2.617784e-10
X4       1338773 9.984934e-153    692.99391 9.982400e-153
X5       3356376  3.635373e-36    157.68031  3.634930e-36
X6       3186599  6.421293e-25    106.27424  6.420576e-25
X7       3116780  2.943772e-19     80.47539  2.943480e-19
X8       2999690  5.374166e-14     56.58809  5.373639e-14

############## FEATURES SIGNIFICANCE | LASSO MODEL ###############

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6772  -0.1797  -0.1791  -0.1789   0.9085

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.790e-01  5.061e-03  35.366  < 2e-16 ***
X1           7.747e-05  6.026e-05   1.286    0.199
X2          -6.539e-06  4.873e-06  -1.342    0.180
X3           5.390e-04  7.029e-04   0.767    0.443
X4           2.174e-05  5.283e-06   4.114 3.94e-05 ***
X5           3.319e-03  3.802e-03   0.873    0.383
X6           6.558e-04  1.777e-03   0.369    0.712
X7           4.881e-06  3.095e-05   0.158    0.875
X8          -1.834e-06  1.958e-06  -0.937    0.349
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.1477158)

    Null deviance: 895.37  on 6044  degrees of freedom
Residual deviance: 891.61  on 6036  degrees of freedom
```

However, I noticed that data results were influenced by the presence of outliers. Outlier is a term used in statistics to define, in a set of observations, an anomalous and aberrant value. A value therefore clearly distant from the other available observations. Casey and Bartczak (1985) define an outlier as a company which any ratio in any year was more than four standard deviations from its group mean. Outliers can cause problems for any tool, Linear Regression has been particularly noted to be extremely sensitive to outliers in at least two of the reviewed studies (Kristóf and Virág, 2012; Tsai and Cheng 2012), and Multi discriminant analysis has been moderately affected by the outliers respect to Artificial intelligence tools which have been less affected. Outlier effects are normally reduced by normalizing variables by industry average (McKee 2000). Such normalization has however been found to reduce accuracy of models (Tam and Kiang, 1992; Jo et al., 1997).

For this reason, I conducted a second analysis in which the outliers were replaced with the median of the values. The median is a number in statistics that tells you where the middle of a data set is (statisticshowto.datasciencecentral.com) and in this case it has been used for data approximation.

Therefore, the second restrictive assumption of the model is the normalization of the abnormal values with the median to reach an optimal performance.

From this second test we came out with a totally different result **(Image 3.4).**

Image 3.4 Statistical Result of the Second Test

```
   wilcoxon_test          p_w kruskal_test          p_k
X1       2955086 1.372352e-06    23.319128 1.372285e-06
X2       2706268          NaN          NaN          NaN
X3       2895073 2.177727e-04    13.671239 2.177643e-04
X4       1712046 1.738937e-83   374.739839 1.738608e-83
X5       3409170 1.242736e-42   187.288015 1.242569e-42
X6       2833106 5.228926e-05    16.363381 5.228570e-05
X7       2729270 9.989859e-02     2.707279 9.989122e-02
X8       2706268          NaN          NaN          NaN

############## FEATURES SIGNIFICANCE | LASSO MODEL ###############

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.36086  -0.23030  -0.15993   0.01259   1.15498

Coefficients: (2 not defined because of singularities)
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.313661   0.007958  39.412  < 2e-16 ***
X1          -0.212897   0.046656  -4.563 5.14e-06 ***
X2                 NA         NA      NA       NA
X3          -0.373741   0.319485  -1.170  0.24212
X4           0.237778   0.012285  19.356  < 2e-16 ***
X5          -0.906767   0.112914  -8.031 1.16e-15 ***
X6          -3.570894   1.023669  -3.488  0.00049 ***
X7          -2.239898   5.599713  -0.400  0.68917
X8                 NA         NA      NA       NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.1359608)

    Null deviance: 895.37  on 6044  degrees of freedom
```

The result from the test shows that the following variables are significant:

- X1 - Working Capital / Total Asset
- X4 - Book Value of Equity / Total Liabilities
- X5 – Sales / Total Asset

- X6 – Cash Flow from Operation / Total Asset

As a matter of fact, their P-Value is below 0,1%, thus, the relative contribution of these variable is important for detecting bankruptcy potential. These variables indicate extremely significant difference among the two groups, failed and non-failed firms.

This result is more reliable than the previous one because it indicates that the model has a discriminant power in line with the one of Altman. Indeed, four of eight variables are significant.
However, our interest is focused on the significance level of X6 (Operating Cash Flow/ Total Assets). This ratio is one of the new variables introduced in the model that comes from the cash flow statement. This result is important because the significatively of this ratio supports the thesis of my paper. As a matter of fact, if the variable calculated as Cash Flow from Operations divided by Total Assets is significant for our statistical test, this mean that one ratio calculated with data from the cash flow statement has a discriminant power and contributes in detecting bankruptcy potential. In other words, the ability to generate operating cash flow from the asset side is a key parameter to predict the failure of an Italian financial service company.

3.4 Empirical Results

The result of the analysis indicates that variable given by the cash flow statement is significant. Our significant ratio is X6, CFFO/TA. This result demonstrates that cash flow components is relevant for bankruptcy prediction. More precisely, the ability to generate cash from the asset side assets (provided by both creditors and stockholders of the firm) is a key figure to observe when detecting for the financial stability of Italian financial companies, and more precisely, for their probability to filed for bankruptcy within the next two years.

As we previously mentioned, Operating Cash Flow to Total Assets or cash flow return is similar to Altman's EBIT to Total Asset measure, however net operating cash flow provides a more relevant measure of a firm's solvency, financial viability and operating performance. Indeed, reported earnings are systematically managed by companies, whereas operating cash flows are relatively hard to manipulate because they do not involve any type of accounting allocations, accruals or deferrals. Therefore, operating cash flow provides a relatively more reliable and objective operating performance measure (Jones and Belkoui, 2010).

This ratio also contributes to the evaluation of financial flexibility. Financial flexibility can be viewed as the ability of the company to generate enough cash internally to react to unforeseen issues and exploit profitable opportunities. Moreover, an assessment of a firm's ability to survive an unexpected drop in revenues. In general, the higher the ratio, the greater the efficiency of the use of assets and the better the firm's financial position (Rojoub et al., 1995).

If we observe a low level of CFO/TA ratio, representing a weak ability of the company to generate cash from its assets, this should be considered as an alert for financial distress. Indeed, without an adequate level of liquidity, the company will probably need to loan more money

This analysis allows me to say that, at the end, if we combine this X6 ratio with other accrual-based information, we are able to predict bankruptcy better than considering only data taken from the balance sheet and from the income statement. Truly, we can say that for the S.p.A companies, belonging to the financial service industry, in Italy.

CHAPTER IV

Final Considerations

4.1 Conclusive Remarks

Cash flow statement represent a relevant tool for the bankruptcy prediction analysis. In the last years, the need to have adequate financial prediction model, in order to overcome the crisis and to maintain the going concern, has promoted restructuring processes (Pollio, 2013; Paolone and Pozzoli, 2018). "Static" analysis of financial statements through accounting ratios started in the last century. Many models were developed with the aim of estimating the probability of bankruptcy. Among the most popular, Beaver's model with his univariate approach and Altman's Z-score model with the Multivariate analysis. The last one provided an enormous contribute and became the most used and reliable model for bankruptcy prediction. Other statistical models were implemented in the following years. However, the great limitation of these models is the use of "static" information based on the accounting income statements. Indeed, the statement of balance sheet and income statement do not provide a "dynamic" and monetary analysis, because they refer to a single point in time, that is the balance sheet date.

Altman uses the working capital as one of his most important indicators. Therefore, we should believe that if current assets, which include cash, credit and inventory, are greater than current liabilities, that is, short term debts, there is no reason to concern about financial distress. Hoverer, we probably go wrong. Indeed, cash is the only asset that pays debts, while we never know when credit and inventory will be converted in cash. Moreover, this ratio does not consider the presence of long-term debt, which may cause problem of insolvency.

Indicators like working capital present a scarce predictive ability since they can be "false positive" for the insolvency estimation.

Cash flow statement provides more reliable measures for the bankruptcy prediction, in particular, cash flow from operations, because it represents the flow of changes in other statements over a period of time (Mckee, 200). Above all, the result of my analysis shows that we cannot ignore from bankruptcy prediction models the ratio FCFO/TA.

Cash flow statement has the ability to communicate data and information required to evaluate the financial soundness and the liquidity situation.

Recently, the regulatory body has recognized the importance of the cash flow statement in the Italian context, with a great step forward in terms of disclosure. As a matter of fact, with Legislative Decree 139/2015, all Italian companies, with the exception of those that prepare the financial statements in abbreviated form and of micro-companies, have the obligation to present the statement of changes in cash flows, the statement within which the only monetary component used as a reference is represented by "Cash Available" and no longer by "Net Working Capital". The attention to "Cash and cash equivalents" as a reference resource is to guarantee an acceptable level of reliability and greater concreteness (being the "cash" a "certain" resource, perhaps the only one, not susceptible to subjective evaluations) with respect to other economic variables without objectivity in their assessment and, very often, subject to distortions in value.

Among the studies concerning bankruptcy prediction, some of their authors (Paolone and Pozzoli, 2017) tested the Altman's model and recognized the limited predictive ability of the accrual accounting-based information. However, they do not suggest new indicators that will boost the predictive ability of the model, especially in Italy. Moreover, they generally tested the model in the manufacturing sector

This was the purpose of my paper, to analyze the financial variables which affect to financial distress and to develop a suggestion for improving the capacity to anticipate business failure with an accounting approach. Therefore, my contribution to researchers is the evidence that accounting statements are not the only documents to analyze for evaluating the financial soundness of a company. Indeed, cash flow from operation to total asset is an important indicator that should be carefully observed when detecting for financial stability of Italian financial companies publicly listed by shares (S.p.A). I considered one of the least analyzed industry, the financial service industry, to enrich the literature with a different context of analysis.

4.1 Limitations and Suggestions for Further Research

Despite the contribution given by my empirical analysis, the present work can be improved. There are some limitations that may represent a starting point for future studies. As a matter of fact, my work is limited to Italian S.p.A. companies, belonging the financial services sector, not listed in any stock exchange. What about the rest? Are we going to obtain the same result if we change the sample data considering a wider range of companies?

Future researches may enlarge the scope of application, for instance by considering other industries, such as the service industry, which is still less analyzed than manufacturing sector. Then, new studies may adapt the model to more countries than Italy, in order to develop a model suitable worldwide. They may sample listed companies or Limited Liability Companies (S.r.l), instead of S.p.A, or they may consider more years for the analysis.

Moreover, since I introduced just three accounting ratios from cash flow statement, (CFFO/TA, CFFO/TL, CFFO/S), it is possible to persist with the same logic of my paper by introducing different cash flow indicators. For instance, the ratio between Cash flow from operation and current liabilities, may have an impact on the predictive ability of bankruptcy prediction models, and many other ratios worth to be investigated.

Finally, an alternative bankruptcy predictive model should take information from the governance, social, human or environmental indicators. Indeed, there are many "non-financial" measures of performance that may represent an alert, which nowadays, are becoming more and more relevant for the business success. According to a new report of Datamaran, financial services companies are increasingly posing more emphasis on climate change on their disclosure. Climate change is mainly mentioned in the context of long-term risks, rather than in recognition of the more imminent effects to business. Additionally, by 2022, the report on climate-related risks and opportunities, will be a mandatory requirement for all listed companies and large asset owners in the U.K.

Those are just ideas to improve the existing traditional models that rely only on the accrual accounting-based data, which sometimes are not so accurate for predicating bankruptcy, or they simply need to be combined with other kind of information.

4.2 Practical and Theoretical Implications

As previously said, this work is important because it proves that cash flow information helps to predict and anticipate business failure, in a specific context and with a specific sample of companies, in this case, the Italian S.p.A not listed financial services companies.

From a practical point of view, this paper implies that companies need to become more cautious about their liquidity situations, and they should consider that financial analysts look at these cash flow indicators to generate grades or credit decisions. As a matter of fact, unhealthy companies generally experience decreasing cash flow from operation one or two years before they filed for bankruptcy (Arlov O. et al.).

In order to avoid the next financial crisis, financial service firms should incorporate financial stability directly by carefully managing their cash inflows and outflows.

Moreover, this paper is particularly relevant for financial analyst who develop statistical models of bankruptcy prediction, since they should consider adding cash flow indicators.

Consequently, I propose to include the ratio CFFO/TA, Cash Flow from Operation to Total Asset, in a bankruptcy prediction model, since I believe that together with the other economic ratios, the model is able to generate a more reliable measure of financial soundness and to better discriminate bankrupted firms from non-bankrupted firms.

To conclude, with both an economic and financial perspective, financial analysts should develop a more robust multivariate bankruptcy prediction model, which include both accrual accounting ratios and cash flow ratios. Then, models should develop a score similar to the one proposed by Altman, to define if a company is in the Safe, Grey or Distress zone.

Finally, the model should be suitable for many business sectors, rather than just for the manufacturing one.

SUMMARY

In the latest decade, academic researchers concerned about defining different status of Corporate Financial Distress and above all, about studying models to predict the Bankruptcy of companies.

Avoiding a business failure is still a main concern not only for the failing company, but also for its employees, stakeholders, linked companies, and for the global economic.

As a matter of fact, big corporate failure phenomenon in the 90's generated several consequences worldwide and drove the wave of bankruptcy prediction studies.

Bankruptcy prediction models have been considered an advanced tool for financial analyst, and their reliability was tested with many empirical analyses, showing high predictive ability. However, the existing literature is not homogenous and rich of dissimilar opinions.

Some models take in consideration market information, as the company's share prices, for evaluating the likelihood of a failure, some others, I would say, the vast majority, analyze accounting ratios from the financial statements, namely the balance sheet and the income statement. Edward Altman is considered the father of these bankruptcy prediction studies based on accounting data, since he delivered the most used method, which provides a score capable of discriminating companies in different soundness status.

Beside these models, many other with different techniques were developed over the years, including modern researches on the use of Artificial Intelligence for this purpose (Neural Network, Decision Trees, Support Vector Machine, Case-based Reasoning and Rough Set). While, just to mention few of the most traditional noted one: Beaver's univariate model, Ohlson's Logit model and Zmijewski's technique. Each of them highly contributes to the vast literature of bankruptcy prediction studies.

Business failure can occur due to external causes, meaning the macro-economic factors, when global economic condition or the industry performance experience a downturn; it may arise due to the competitive landscape, or due to environmental and regulatory changes. Nevertheless, failure commonly generates from the micro-economic variables, such as the company's age and business lifecycle; the corporate social responsibility; the bad management and investment decisions.

Corporate financial distress indicates a deteriorating economic condition of a company. Generally, a long-lasting bad economic situation leads to the default when it is associated

with the term “insolvency”. When a company results as insolvent, it means that is experiencing problem of liquidity and thus, problem to pay off its debts. The inability of a corporation to generate cash over time may force the firm to borrow more money, or to dispose of its capital investments to meet its obligations. Therefore, when there is no way for a restructuring procedure or a bailout process to save the company, its dead occurs.

Even though it could be so evident the direct link between the liquidity and the possibility of bankruptcy, not everyone in their studies focused the attention on the pure “cash”.

Cash is the only asset used to buys things, pays wages, salaries, compensates stockholders and face unexpected adverse events.

The definition of "Cash is King" represents in a clear and effective manner the role that the monetary availability covers in the entire corporate system, as well as the ability to monitor the status of the system itself. The document that identifies the "cash" component in all its facets, is the Cash Flow Statement.

With the Legislative Decree 139/2015, all Italian companies, with the exception of those that prepare the financial statements in abbreviated form and of micro-companies, are obliged to present the statement of changes in cash flows, the table in which, the only component with monetary nature used as a reference is represented by the "Cash and cash equivalents" and no longer by the "Net Working Capital".

Differently from the balance and the income statement, cash flow statement provides “non static” information, showing the dynamicity of the business with its inflows and outflow during a period of time, while the other documents only present a picture of the economic condition at a specific point of time. Financial statements are generally subjected to earnings management techniques and allocations by managers; thus, financial information may be distorted from reality. The goal of shifting the focus to "Liquidity Availability" as a reference resource is to ensure an acceptable level of reliability and greater concreteness with respect to other economic quantities without objectivity in their measurement and, very often, subject to distortions in value.

The aim of this work is to contribute to the literature that support the predictive ability of cash flow data by developing a bankruptcy prediction model which include both accrual accounting-based ratios and cash flow ratios.

In particular, this paper takes inspiration from the work of Paolone and Pozzoli (2017), which demonstrated the scarce predictive power of Altman model when analyzing Italian Manufacturing companies. To continue with the previous findings, I selected as sample data

Italian S.p.A companies, which belong to the financial service industry. The choose of the financial sector has been made for the scarcity of related studies in that industry. The sample is then divided in two groups: Group 1 consists of 4952 active companies while group 2 consists of 2623 bankrupted firms filed under bankruptcy petition in the period 2016 – 2017.

The analysis was conducted by collecting data from AIDA financial database for Italian companies. The interested data are selected in order to fill in the accounting ratios needed. The model was composed by eight financial ratios: five from the balance sheet and income statement, traditionally used by the Altman's model, namely, Working Capital to Total Asset (X1); Retained Earnings to Total Asset (X2); EBIT to Total Asset (X3); Book Value of Equity to Total Liabilities (X4); Sales to Total Assets (X5).

In addition to this, I included three more ratios taken from the cash flow statement: Cash Flow from Operation to Total Asset (X6); Cash flow from Operation to Total Liabilities (X7); Cash Flow from Operation to Sales (X8).

After the computation of the eight financial ratios for each of the selected firms, I developed a statistical analysis using STATA software. The aim of the analysis was to discover which of the previously mentioned ratios contribute the most in discriminating firms between bankrupted and non-bankrupted status. To reach this conclusion, I investigated the significance level of each variable in the model. To be clear, a variable is significant when its P-Value is below 0,1%.

The result of the statistical test show that variables X1, X4, X5 and more interestingly X6, are significant. The evidence that variable X6, Cash flow from Operation to Total Asset is significant, support the thesis of the relevance of cash flow information for predicting bankruptcy. Therefore, the ability to generate cash from the asset side is an important indicator to evaluate the financial stability of a company. For this reason, I believe that, by including this new ratio in the traditional bankruptcy prediction models, it is possible to improve their predictive power.

However, my study explicitly recognizes limitations and assumptions when developing the model. As a matter of fact, the analysis is limited to the Italian financial service industry of S.p.A not listed companies. Therefore, there a lot of opportunities for future researches, to follow the same logic and expand the scope of application.

To conclude, the importance of cash flow data has been proven by my empirical study, with one new ratio demonstrating its discriminatory power. Consequentially, bankruptcy prediction models require to be updated with cash flow ratios, combined with accrual accounting-based ratios. In that way, models can provide a more reliable and objective alert of financial distress and increase the possibility to anticipate corporate bankruptcy.

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