MSC PROGRAMME IN BANKING AND FINANCE

MASTER THESIS

SMES’s BANK FINANCING IN EUROPE: CREDIT LOAN CRITERIA AND EVALUATION METHODS

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Abstract

The study aims to provide a better understanding of SME default risk modeling in European Union (EU). The determinants of financial leverage decisions are different for micro, small, medium and large firms. The main objective of this dissertation is the review of the most important models and techniques developed through all these decades, especially the implementation of the revised Z-Score credit technique created by Altman (2000). This model is based on financial statement analysis of corporations in order to assess the creditworthiness of them and identify the financial problems of the firms by classifying them into defaulted or non-defaulted. The data collected for the implementation of this model refer to manufacturing and non-manufacturing small and medium-sized corporations of the private sector in Europe.

Being able to predict corporate failure is the most interesting matter for all banks. The process followed, included a correlation matrix and econometric models such as Altman z-score, probit and logit regression models, helped us to verify our findings and to explain the probability of a firm raising debt or avoiding bankruptcy. Finally, our findings strongly indicate the exact effect of each parameter to the firms’ financial activity and must be seen as a complementary supplement in bank’s assessment of SMEs’ default probability.

Key Words: Altman Z-Score, Bankruptcy, Discriminant Analysis, Logistic Regression, Credit risk, Default risk, Credit scoring models
Chapter 1

Introduction

Under the term “default risk”, we refer to firm’s inability to fulfill its own financial obligations such as refund for borrowed capital towards the banks (Lotz & Schlogl, 2000). Nowadays, banks are struggling in a move competitive and demanding environment as they have to face credit and operational risks in their portfolios. Under the directives of New Basel II Capital Accord (Basel Committee On banking Supervision, 2006), better known as “Basel II”, banks have to adjust to new rules concerning the credit risk markets and more precisely to follow new approaches such as Internal Ratings Approach (IRB) which is a large part of the New Basel II Capital Accord (Basel Committee, 2006). The new innovations applied by the Basel Committee on Banking Supervision have meaningful consequences on credit risk management decisions for capital lending to SMEs.

Under this new regime, banks are obliged to implement more complicated and elaborated methods in order to interpret in more detail the specific individual characteristics of credit risk for each firm. The implementation of the IRB Approach is challenging due to the fact that the banks have to take internal actions in assessing the credit risk profile of firms and especially those which haven’t got an assigned rating grade by an external rating agency such as Standard & Poor’s or Moody’s. For those firms that have not a rating by an agency, banks have to calculate the default probability (PD) on their own (Altman & Sabato, 2005). These firms are mainly the small and medium sized enterprises (SMEs).

This study analyzes the finance of Small and Medium Enterprises by European banks using credit loan criteria and different evaluation methods. The aim of our research is to find the reasons why banks-in the EU mainly- are in the pursuit of

1The bank loans are, for SMEs, the most important source of fund to finance corporate investments
2Data published by rating agencies show that the size of an enterprise is also a variable that impacts on default risk as default rates are higher for small-medium sized enterprises.
3According to the EU, SME is defined to have less than 250 employees and more than 50 and a turnover of less than 50 million € or a balance sheet of less than 43 million €.
financing European SMEs and to which extend the European banks lend to the SMEs. Our analysis is based on initial Altman’s Z-score model (1968) and its revised one (2000) that makes use of a set of financial ratios which measure the creditworthiness and the possibility of bankruptcy of the firm. The aim of this following procedure is to evaluate the significance of efficiency in predicting firm defaults over and above of that explained by financial factors. We will try to measure with the most effective model the finance health of firms by constructing a scoring rule that attaches a numerical value to each SME and analyze the factors that influence the adopting approaches by the banks to lend to SMES.
Chapter 2

Literature review

Beaver (1966) was the first who studied the effect of individual financial ratios and accounting data on default (six financial ratios from among 30 ratios were selected as best indicators of performance) and the conclusion that ratio analysis is useful in bankruptcy prediction. Altman (1968) was the pioneer of the statistical credit risk models. He expanded Beaver’s model to a multivariate context and developed the Z-score model:

\[ Z - score = 1,2 \left( \frac{Working\ Capital}{Total\ Assets} \right) + 1,4 \left( \frac{Retained\ Earnings}{Total\ Assets} \right) + 3,3 \left( \frac{EBIT}{Total\ Assets} \right) \]

\[ + 0,6 \left( \frac{Market\ Value\ of\ Equity}{Total\ Liabilities} \right) + 1,0 \left( \frac{Sales}{Total\ Assets} \right) \]

For the first time he managed to analyze specific multiple financial ratios at the same time in a bankruptcy prediction framework as part of the Z-score model. He succeeded in analyzing the influence of various factors, mainly financial ratios on the creditworthiness of business. He wanted to point out that if a selected set of factors which are considered to have a significant impact on whether or not firm details, are combined and measured appropriately will give us a score that will help us in the credit worthiness assessment of the firm (Altman, 1968). He used Linear Discriminant Analysis (LDA) to generate a single composite score (Ohlson, 1980). Ohlson (1980) used Logistic Regression to come up a default risk model known as O-Score. The variables of O-Score were the size of firm, the measure of financial structure, measure of performance and measure of current liquidity.

As mentioned before, Altman’s model was the basis for many studies all these decades but much volatility in financial information models and general accepted
accounting practices deteriorated its predictive ability. Altman revised its model in order to maximise its accuracy and in 1977 introduced the Zeta model. The MDA method dominated the economic field until the 1980’s (Altman, 1977). The most usual forms of MDA are the linear and quadric MDA. Later on, its use was limited and substituted from other less demanding statistic techniques like Logit (LA) and Probit (PA) models. All the above techniques led to other predictive models (Doumpos & Zopounidis, 2000) which included suitable variable combinations of discriminating businesses into defaulted or not.

In this study, the major aspects of statistical credit risk models, mostly logistic ones as tools of measuring the default probability of SME’s exposure, are discussed. Such models are the so called Z-score model by Altman (1968) and its revised form for EU SMEs by Altman and Sabato (2006). Altman’s (1968) Z-score was the first model that analyzed financial ratios taken by the financial data of firms in order to assess the creditworthiness of a firm and classify the enterprises as defaulted or non-defaulted. The model was based on observations on 33 defaulted and 33 non-defaulted manufacturing firms for the period 1946-1965 (Altman, 1968).

Bankruptcy prediction models were by the 1960 and 1970 a matter of high interest. Some years after the development of the Z score model, in 1974 Merton developed a model in order to predict whether a financial firm will go bankrupt in sometime soon. In particular, the model he developed used the equity and the debt of the firm under study to estimate its value. Merton claimed that an equity position can be viewed as if it were a portfolio of three securities: a long position in the firm’s assets, a short position in a risk-free bond, and a long position on a put option that gives stockholders the right to “put” the firm’s assets onto debt holders in lieu of paying the promised interest and principal (Goldstein, 2010). Thus the model can estimate the firm’s liability and enlighten the matter of potential bankruptcy. Despite the universal acceptance of the model, it seems to have some important drawbacks as the high degree of clustering of defaults during recessions and the difficulty in explaining why credit risk rates are often high when the model estimates low default rates.
Despite the fact that the technique applied by Altman (1968) has since become outdated in terms of Basel II requirements, many other authors use the original Z-score model as a benchmark for assessing SME’s performance. Altman and Sabato (2006) used a sample of nearly 2,000 companies of which 120 were defaulted (from 1994 to 2002) and created a logistic model designed for US SMES’s purposes. Their aim was to show how important is to have a separate model for evaluating the rating of an SME instead of using a model that is also used for bigger companies (Altman & Sabato, 2006).

According to Altman and Sabato (2006), banks can minimize the required capital in accordance with Basel II by taking into consideration the differences that SMEs and large firms have between each other. The proprietary Risk Calc model by Moody’s KMV (2000) also contributed in the PD estimation of unrated private companies. The basic point of the KMV model is that when the market value of a firm drops below a certain level, the firm will default on its obligations. It was not only a provider of credit risk commercial management solutions but also serves the purpose of describing the credit risk differences between countries.

Altman’s model is a long discussed and studied one by academics and analysts. There are multiple studies concerning its usefulness. One of such studies is the one conducted by Gerantonis et al. (2009) about whether the Z score model can predict bankruptcy up to three years earlier before it really takes place. Examining firms listed on the Athens Stock exchange during the period 2002-2008, bankrupt or suspended to be bankrupt during this period, the analysts find that Altman’s Z score model can indeed predict bankruptcy 2 years before it does actually happen. Additionally, they conclude that the model can predict bankruptcy correctly in 54% of the cases one year before taking place.

More recent studies on such bankruptcy prediction models show that even if those old models are highly used and even recommended today, there are some facts showing these models should not be used in all nowadays’ sectors. Martin et al. (2011) state that when it comes to services and information technology companies, the application of such models is not so accurate as these ones were developed for
manufacturing companies. Today, the service and information technology companies are characterized by a different set of financial norms than the manufacturing companies, thus making these models incapable of estimating properly the possibility of bankruptcy. Martin et al (2011) used Z score model and data minding algorithm to develop another one, the Business Intelligence (BI) model, in order to predict if an information technology firm is going bankrupt. This is actually an updated form of Altman’s Z score model, as it uses its structure for firms having too much data to process in order to characterize the firm as default or non-default.

Another study concerning Altman’s Z score model is the one by Miller (2009). The researcher examined the performance of Z score and another model, Distance to Default model, in order to find out the ability of these much used models to predict bankruptcy before it takes place, their ability to predict right and the stability of their ratings. His findings agree with Martin et al’s (2011) aspect that the Z score is not meant to be used in non manufacturing companies, even if it commonly used in such firms. Additionally, he found out that Altman’s model has more stable ratings of bankruptcy prediction that the Distance to Default model, but the latter is better in predicting accurately under nowadays’ circumstances.

Grice and Ingram (2001) also examined Altman’s Z score performance in the current business world. The researchers state that this model is the most commonly used for predicting bankruptcy or the tendency towards bankruptcy in most sectors of the economy. They examined whether the model is useful today as it was when firstly developed, whether it should be used in non manufacturing sectors and whether it can predict effectively financial problems and distress a firm might face. They found that the circumstances have changed since Altman developed the model, thus it has not the same usefulness as then. Additionally, as Miller (2009) and Martin et al (2011), they found as that it should be not used in the non manufacturing sectors, even if it actually is. Finally, they found that the Z score can actually predict efficiently whether the firm under study faces financial distress.
Chapter 3

SMEs’ Description

3.1 Definition of SME

The term of a Small Medium Enterprise (SME) contains a large variety of meanings and models consistent with SME statistics methods. The meaning of SME was not standard at Europe before April 1996. The European Commission began to expand different terms of SME during this period. However, the definition of Commission was broadcasted in May 2003, intended four criteria to be categorized as a ‘‘small’’, ‘‘medium’’ and ‘‘very small’’ firm (European Commission, 2003).

Every company should meet the criteria for the number of employees, the total annual turnover, the balance sheet total and the size of investment in assets and independence (Ayyagari, 2003).

- Number of employees who are engaged in full-time work within the firm throughout the full year. Part-timers, workers for seasonal period and those who do not work the full year are treated as part-time workers. The number of employees includes (Ayadi, 2005):
  - Employees
  - Other workers who are inferior to it and regarded to be employees under national law
  - Owner-managers
  - Workers who are occupied with a regular activity in the company and who gain financial benefits arising from it.

- Annual turnover, which is estimated by the difference between the inflows and outflows of a firm during the year. Turnover should not contain value added taxes (VAT) or other indirect taxes (Ayadi, 2005).

- Balance sheet total, regarding to the value of the firm’s assets (Ayadi, 2005).
Independence, which is related with capital and voting rights. The independence of a company there is when a single shareholder has restricted influence. Moreover, it is regarded independent if it does not participate in other companies and no company does not participate in it, or if the company has a holding of less than 25% of the capital or voting rights in one or more other companies do not have a stake of more than 25% of the capital or voting rights in it (Ayadi, 2005).

Table 1: EU definition of a SME

<table>
<thead>
<tr>
<th>Category</th>
<th>Number of employees</th>
<th>Annual turnover</th>
<th>Annual balance sheet total</th>
<th>Independence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Micro</td>
<td>&lt; 10</td>
<td>€ 2 million</td>
<td>€ 2 million</td>
<td>Given by 25% of capital shares held by a third party</td>
</tr>
<tr>
<td>Small</td>
<td>&lt; 50</td>
<td>€ 10 million</td>
<td>€ 10 million</td>
<td></td>
</tr>
<tr>
<td>Medium-sized</td>
<td>&lt; 250</td>
<td>€ 50 million</td>
<td>€ 43 million</td>
<td></td>
</tr>
</tbody>
</table>


As table 1 displays, medium-sized enterprises are determined as those that occupy more than 50 but fewer than 250 persons and whose annual turnover is more than €10 million but less than or equal to €50 million or whose annual balance-sheet total is more than €10 million but does not exceed €43 million. Small firms are determined as those that occupy fewer than 50 persons and whose annual turnover or annual balance-sheet total does not exceed €10 million. Micro-enterprises are determined as those that occupy fewer than 10 persons and whose annual turnover or annual balance-sheet total does not exceed €2 million (Ayadi, 2005).

It is essential to comment that while it is mandatory to consider the number of employees, an SME may prefer either the turnover or the balance-sheet ceiling (Ayadi, 2005). However, except of above definitions, SME can be divided into additional three groups (Hauser, 2005):

- Enterprises where the manager and the owner is the same person and decide for short and long-term issues of his firm (type 1 enterprise).
SME where the manager makes the short-term strategic decisions and prepares the long-term decisions. The number of owners includes private investors who are interested in maximization of their profit and consequently the profit of the firm (type 2 enterprise).

Firms belonging to firm groups. There is not maximization of profits within the firm but elsewhere (type 3 enterprise).

### 3.2 Special characteristics of SMEs

Generally SME are diverse. There are many types of them. However, they are related with the following characteristics:\(^4\):

- They are related of individual motives and skills.
  
  SME are created as a means of earning livelihood by a single entrepreneur or a small group of entrepreneurs. These contain trading, retailing or manufacturing services.

- Their functions have greater flexibility.
  
  There are hierarchical structures due to the small number of owners and the direct involvement of them. These ensure greater operational flexibility. Making decisions about price, product and other decisions related to market conditions is faster.

- Their production is generally low at cost.
  
  SMEs have lower overheads resulting to lower cost of production.

- They can adjust technology with high propensity
  
  SMEs are capable of adopting and internalizing the technology being used by them.

- They have high capacity for exports.
  
  The skills of SME in innovation and improvisation are very important. They are also capable of capturing export markets where volumes are not huge by being able to meet their needs.

- SME promote employment.

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They offer jobs creating positions up to 80% of the population globally and are able to provide more jobs for every unit of investment in comparison with bigger firms.

- They are able to utilize available human & material resources.

  SMEs offer jobs in the society and utilize manpower whereas available locally. They become better with materials and focus on a small range of products or services which are available on the local domestic market.

- Reduction of regional imbalances.

  SMEs enjoy the flexibility of location comparing with large industries where the operation of functions is more difficult and an informed and strict observance of regulations is evident. SMEs have the ability to spread easily at specific location but this spread of SMEs increases the creation from policies either national or regional.

- They have owners or managers without many business skills and with little formal business experience. Many SME have the owner as the only person in a managerial position. They haven’t specialist experts whose job is to do one task only.

- They have a lack of cash and financial resources. Also, they have human resource limitations because all personal assets, including the owner's home, committed as security for the business.

- They have a lack of cash and financial resources. Also, they have human resource limitations because all personal assets, including the owner's home, committed as security for the business.

- They have compliance risk with higher likelihood of tax evasion, operating outside tax net and they face high costs of compliance relative to their turnover, profits.

### 3.3 The importance of the SME sector in Europe

The high position of SMEs to the European economy is well acknowledged. SMEs are regarded to have an important role in the economy, they are an important source of economic growth, innovation, flexibility and they can be also adjust easily to variations of demand and supply situations. They are the backbone of our society. In addition, SMEs promote employment, enable varying economic activity and contribute significantly to exports and trade. (Brookfield, 2001). It is essential to make
sure that the finance of SMEs is not difficult because of severe capital rules, but their restricted size and reputation does not enable the finance in capital markets (Ayadi, 2005).

There are many SME proponents on significance of SME and there are many who do not support SME but emphasize the advantages of large companies. According to SME supporters, SME increase competition and entrepreneurship and their contribution on efficiency of economy, innovation and productivity growth is important. (Klapper & Sulla, 2002).

On the other hand, there are many who support that large companies take advantage of economies of scale and take on responsibility the fixed costs in relation with research and development (R&D) with favorable productivity impacts. Also, there is the opinion that large enterprises get to invest more in developing scientific procedures, while SME do not contribute as much in the development and progress of the sector they belong to, due to limited funds available (McAdam & Reid, 2001).

It cannot be argued how great the significant of SME is in local and global economy as well. “SMEs employ a large part of the population, for example, between 2001 and 2003 in the EU, they were the most significant force in driving job growth than their “counterparties”” (Schmiemann, 2006). The SMEs are considered to be in the interest of banks (as the PD is a vital element in the measurement of capital requirements) because if they can find and implement a model that has the capability to quantify and predict the firm’s default probability in great accuracy, then the bank will be in the position to price the loans correctly and take the correct credit risk decisions. The following table gives the size structure of SMEs in the EU for the year 2003:
Table 2: Size structure of firms in the EU

<table>
<thead>
<tr>
<th>Firm size group by number of employees</th>
<th>Percentage of firms</th>
<th>Percentage of total employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-9</td>
<td>91,25%</td>
<td>28,8%</td>
</tr>
<tr>
<td>10-50</td>
<td>7,4%</td>
<td>20,50%</td>
</tr>
<tr>
<td>50-250</td>
<td>1,1%</td>
<td>66,2%</td>
</tr>
<tr>
<td>Less than 250</td>
<td>99,75%</td>
<td>66,20%</td>
</tr>
</tbody>
</table>


As we can see from the above table, SMEs represent over than 90 percent of all companies and employ at least 65% of the workforce that’s why the banks credit portfolio exposure is high. A problem that most banks are dealing regarding the SMEs is that most of these firms do not have a rating grade that would help banks to evaluate the creditworthiness in terms of PD. The only thing that banks can handle is the SME’s accounting data being utilized in Basel II context. It has been recognized that firm’s market information is more reliable and accurate that accounting data. As a result, the challenge of banks is to find a way to qualify credit risk without acknowledge of market data or external agency ratings.

**3.4 Sources of SME financing**

Financing a company is one of the major problems everyday managers or accountants deal with when it comes to decision making. The need for capital is the most common subject in business meetings. Even if nowadays there are plenty of sources of finance for firms worldwide, small and medium enterprises (SME) have to carefully examine their choices when deciding on how to be funded. In order to grow, a firm is needed to be able to depend on equity and debt. Thus SMEs have a financial growth cycle in which financial necessities and options change as the business grows and becomes more transparent (Pissarides, 2000).
There are multiple sources of finance that SME can choose from in order to get the necessary funding. In general, a company chooses from those various sources of finance depending not only on the amount of capital required for its purposes, but also on the terms that it is granted (Brookfield, 2001). Sources of finance can be divided into the following two categories; internal and external ones.

3.4.1 Internal sources of finance

When it comes to internal financing, SMEs can use one of the following ways to raise funds (European Commission, 2009):

- **Company’s profits**: when a firm has profitability at the end of a financial year, then it has two choices; give shareholders dividends according to the shares they own, or keep the profits and re-invest them when the firm needs capital. The only problem arising in this source of finance is that the shareholders have to agree to receive lower dividends in order for the company to preserve the profits and invest them when needed. Shareholders’ reaction to this decision is always unpredictable, as many of them simply care about their personal goals and ignore the company’s welfare.

- **Working Capital**: working capital consists of the money used for a company’s everyday routine activities, such as salaries and everyday payments. It is equal to current Assets after subtracting Current Liabilities\(^5\).

In order for a company to increase its working capital, it can either collect payments from customers, or have stricter terms in credit policy. Another choice is to delay payments to suppliers, although this strategy is a rather risky one, as the suppliers may have strict terms when getting paid later than expected. Whichever decision and strategy the SME implements, it is vital to ensure that managers responsible for this

source of finance know how to do so, as when working capital management is done effectively, the firm can secure cash.

- **Sale of assets**: there are some cases that a firm maintains assets that are not actually used. Then, the company can rent or sell these assets and use the capital received for further funding.

### 3.4.2 External sources of finance

When a SME raises funding by borrowing from sources outer of the firm, it basically has two choices; whether to use a short-term source of external finance or a long-term one (OECD, 2006).

#### 3.4.2.1 Short-term external financing sources

- **Factoring**: Finance of the production cycle is not easy for small enterprises as they do not have access to bank credit. The firm, when realizing that the amount of debt customers or other stakeholders own to the company is big enough or difficult to be managed and collected, it sells this debt to another company, the factor, which is then responsible for managing and collecting these amounts receivable. The factor has two choices; whether agree on buying the whole debt and just pay the firm an amount of it, or manage the debt, receive it in the name of the company, give it back and receive a percentage of the amount received as its payment. Either way, factoring is a very effective way to gain cash for a SME (Klapper, 2006).

- **Loans**: in the case of a short-term loan from a commercial bank, the firm receives the amount set by the bank and its managers, agreeing to pay a fixed or a floating charge (known as the interest rate), which usually is a serious amount of capital in relation to the loan itself (OECD, 2006).
• **Overdraft**: in case a SME needs cash, there is always the choice of overdraft. In that case, the firm can withdraw from its bank accounts all its money, so that the balance of the account turns to zero. In that case, the firm needs to be aware of the fact that high charges are usually imposed on such decisions (OECD, 2006).

• **Trade credit**: the company asks or lets its suppliers know that it will be paying back its debt in a longer period of time than initially planned. Even if this method can offer the firm liquidity for short-term time periods, the suppliers usually ask for further charges because of this delay. The difference with working capital is that in case of the latter, the SME does delay payments to suppliers without making any kind of agreement with them. In trading credit, the SME tries to make an agreement for paying back later (OECD, 2006).

### 3.4.2.2 Long-term external financing sources

There are multiple long term external financing sources available for SMEs:

• **Share Capital**: when a firm needs to raise capital, then under specific conditions and terms, it can sell to the public a percentage of its equity. This percentage is divided into shares, and then sold to the shareholders. Each one of them deserves a dividend (or more than one, depending on the number of shares he has), which is a part of the company’s profits, if the firm has gained profitability within the fiscal year. In case the company decides to keep the whole amount of profit for funding reasons, then the shareholders do not receive dividends. In case the firm, after selling a part of its equity, decides it needs more funding, it can sell further more of its capital. That practically means that the number of shareholders increases, thus their impact and power on the company increases, and at last the company itself loses control. This is why many firms are careful when selling their shares, so as to keep the number of shareholders the smallest possible.

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• **Loan Capital:** consists of debentures, insurance, venture capital, leasing and securitization.

- **Debenture:** this source of long term funding is most commonly known as bond. The firm that needs to raise capital, and fulfills specific requirements, gives all interest parts a written note, claiming that the firm received from them the value of the note, and agrees that till the date it expires, the firm will pay the interest parts (its funders in other words) every year or semi-year a coupon. At the date of expiration, the interest part receives back the capital he gave for buying this note. Though it is thought to be an effective method of funding, only limited companies can use this way to raise funds.

- **Insurance:** The costs of default can be restricted if banks supply a determined amount of loan in order to cover its value. Banks to approve the loan should have collateral. However, there is a problem regarding in collateral. The facts that, products have a short life cycle are blended with large fluctuations and, therefore, property prices decrease the security of collateral. Consequently, the valuation of collateral should be examined to be lower by banks. There are a large number of kinds of insurance to SMEs that contribute to decrease the lender’s risk and offer SME access to credit. Some of these types contain loan or mutual guarantee schemes and export credit insurance (OECD, 2006).

Loan guarantee schemes are provided by governments to SME that lack collateral restricting though the perceived risk of SMEs to the lending institutions. The objectives of these schemes are (Ricupero, 2002):

- Provision of help in small firms to get loans without collateral
- To give courage banks to cope with SMEs
- Provision to banks of to cope with SMEs’ loan portfolios and to lend profitably to SMEs.
On the other hand, there are lots of drawbacks such as moral hazard and adverse selection problems, high administrative costs and inexperienced staff coping with SME loan portfolios. Some of these drawbacks could be resolved. For example, the administrative costs of credit and monitoring SMEs could be declined if business development service (BDS) providers undertake these activities.

Apart from these drawbacks, SME have to deal with many more problems in their effort to gather funding via insurance. The lack of information, or the uncertainty, that characterizes the current financial systems and markets in general has proven to be a hindering factor when it comes to financing (Brookfield, 2001).

Credit insurance is a type of insurance including the risk of the seller when he does not pay after the delivery of his good. It has been used for limiting the risks of foreign markets and is known as export credit insurance. Export credit is a guarantee which is provided by a bank to a foreign buyer who has signed a contract with an exporter. Export credit insurance schemes are beneficial for SMEs seeking to internationalize their activities (Ricupero, 2002).

Venture Capital: Venture capital includes the supplying of investment finance to private small or medium-sized enterprises in the creation of equity. It is long-term risk finance where the basic return to the investor is come from capital earnings rather than dividend income. As a method, it is used by firms that have difficulties securing a bank loan or any other form of funding (Kaplan & Stromberg, 2003). A venture capital fund would make an investment in an SME in a high-growth sector trying to extend its functions. A venture capitalist will require a high expected rate of return on investments, to compensate for the high risk. His involvement is generally from two to four years, after which the venture capitalist will either sell the shares of the enterprise on a stock exchange, e.g an initial public offering (IPO) or sell the whole stake in the enterprise, e.g the more established competitor (Ricupero, 2002).
The benefits of a venture capital are the following:

- Venture capitalists are voluntary to receive higher risks than banks in consideration for possibly earnings from the sale of shares in the firm.
- Venture capitalists do not need collateral from borrowers.
- Functioning costs are lower because of loss of high interest rate payments.
- Venture capital is long-term or at least medium-term capital, in regard to short-term loans from banks.

However, there are some disadvantages to venture capital funding (Ricupero, 2002):

- Functioning costs related with lending a small amount do not encourage investors as in traditional bank.
- Equity position: Most venture capital enterprises need the enterprise gives up an equity position to them in return for their funding. This amount is not small meaning that the entrepreneur is not controlling their business.
- Decision making: One of the main problems that many entrepreneurs face when they agree to accept venture capital is the operation of their firm.

The improvement of the financial institutions for SME is important and therefore the European Commission is cooperated with other nations. This cooperation with SME organizations has a result to reduce risks and costs and combine financial and non-financial services. The Commission made specific improvements to the financial environment by arranging the sharing experience and best practice amongst national governments. In addition, the supply of risk capital is vital for the development and growth of innovative SMEs (European Commission, 2008).

Commercial banks, specialized finance firms and other financial instruments offer external debt finance. Financial instruments offer two kinds of credit to SMEs: a) credit cards and credit lines and b) mortgage loans, equipment loans, motor vehicle loans, capital leases and other types of loans. Credit cards and credit lines are used to finance working capital needs. They can be offer a guarantee to one or more owners
the possibility of recourse to the personal wealth of the owners in the case that the loan is not repaid. The different types of loans are used to finance special assets (Ayadi, 2005).

Furthermore, banks create additional measures in order to meliorate the lending of SME and the access to finance. The training and experience of bank staff and the segmentation customers is a measure by banks to better sub serve the SME sector. Also, other mechanisms that uses banks in order to increase the volume and the quality of the services in the SME sector is the use of advanced technologies for reducing costs of lending and the reduction of information asymmetry of SMEs (Ricupero, 2002).

- **Leasing**: It is an agreement between the owner of an asset and the user of the asset. An enterprise can cover its requirements for machinery, equipment, vehicles and real estate thought leasing. Leasing is a way of acquiring an asset without paying cash, taking out a loan. Leasing is, therefore, a form of rental. For the duration of the lease, the lessee makes periodic payments to the lessor, with an underlying interest cost. There are two basic forms of lease: "operating leases" and "finance leases" (Roch, 2005). Leasing is very attractive for many SME when they don’t have enough cash to pay. It enables the company to match expected income and expenditure flows. Moreover, leasing can help the firm to become more productive maintaining its liquidity.

- **Securitization**: Finally, structured finance or securitization is a very important source of financing. Securitization is a risk transfer and a capital market initiative that contribute to increase access to debt finance of SMEs. Via securitization a whole portfolio of loans is transferred (Ricupero, 2002).

Among benefits is that increases the lending capacity for banks and leasing firms and the profitability of SME lending activities due to the rise of capital base. On the other hand, the creation of transaction costs is a drawback that is related with SME securitization. These costs are generated due to the complex nature of securitization.
Chapter 4

Difficulties SMEs face in raising funds

4.1 SME’s constraints to access to finance

It is generally accepted that access to finance plays a significant role in the overall business environment. But also, finance has been cited in many business surveys as one of the main constraints to SMEs’ survival and growth of small and medium-sized enterprises. Inadequacies in approach to finance are fundamental obstacles to SME growth. SME make procreative investments to become expanded their business with financing and secure their competitiveness getting the advanced technologies. Even though their advantages such as the contribution to employment, SMEs have confronted with difficulty in ensuring finance related to large enterprises (Ganbold, 2008).

Traditional commercial banks and investors have disinclined to service SME for a number of different reasons. The causes that SMEs tend to have a high risk profile are the following (Ganbold, 2008):

A. Financial Sector Policy Distortions

The connection of firms to lenders and investors which is caused by the existence of strong financial markets affects SME to approach finance. Governments, in order to embarrass a probable financial failure in markets, interfere in the following ways without results:
➢ High interest rate

The enforcement of high interest rates by government disheartens banks to lend to high-risk borrowers.

➢ State-owned enterprises

Large state-owned enterprises and government infrastructure projects access to bank credit, crowing out non-state enterprises.

➢ Public sector borrowing

Investments in government are safer than investments in unknown SMEs

➢ Legal and regulatory frameworks

The growth of leasing, factoring and venture capital has been restricted because there is the absence of legal and regulatory frameworks (Brookfield, 2001).

B. Lack of Suppliers’ Know-How

➢ Small loan size relative to transaction costs

SME need small amounts of loans in comparison with large enterprises. SME financing are not a lucrative business because there are high administrative costs of lending and investments are needed small amounts of loans.

Many governments and international financial institutions have made an effort to find solutions for the high transaction costs and risks through subsidized credit programs or giving loan guarantee

➢ Difficulty in adopting new lending technologies

Advanced lending technologies have the ability to link the demand with supply of credit. They contain the following:

a) Loan analysis that concentrates on the capability of clients to give constrictive collateral

b) Giving loan to keep high-quality portfolios
c) Regulating mechanisms of management information systems and of
information technology for management and administration of the loan
portfolio

d) Offering large amounts of loans and longer terms for well-performing
borrowers (Ganbold, 2008).

C. Information Asymmetries

When a firm turns to outer sources for funding, the banks need to be certain their
investment will be profitable. In order to be sure, they require all possible information
about the firm’s business plan, its current activities, its future prospects, data about
the new investments the firm has scheduled, and perhaps even more information. The
lack of knowledge of a SME’s activities and effectiveness in general is actually an
obstacle for securing these funds, as the outer financing sources often turn down such
financing decisions as they cannot be certain for the outcome. (Bowen et al, 2009).

D. High Risks of SME Operations

SME functions deal with two basic risks:

➢ Vulnerability and turnover

SME are considered by creditors and investors as high-risk borrowers in relation to
large enterprises because SME are more susceptible to market fluctuations with
high mortality rates and due to their lack of large size, they often have not sufficient
management abilities

➢ Weakness of management

The implementation for credit is confined by weakness in firm management in
many SME. There are many programs that enhance the finance for SME helping
them to become stronger in management and in productivity. (Ganbold, 2008)

According to the above risks, banks are with the part of large corporate borrowers
who offer better business plans, have credit ratings, more confidential financial
information, better chances of success and higher profitability. It is necessary for
banks in order to assume the risk and implement more tightly monitoring measures to charge a commission in lending of SME (Ricupero, 2002).

4.2 Challenges for SMEs

The most small and medium-sized firms face many challenges. They are the following: (European Commission, 2008):

- Administrative and regulatory burden
- Access to finance
- Taxation
- Lack of skills
- Too strong competition
- Late payments
- Access to international markets

According the above challenges, European Commission is trying to make the life easier for SME with many ways (European Commission, 2008).

The European Commission in order to reduce the administrative burden and the legislation to be better and friendly without a lot of regulations propose some targets (European Commission, 2008).

- Business registration should take no more than one week and costs should be reduced.
- Business should be able to report data ‘once and for all’ to public administration.
- Companies should only be expected to provide statistics once in three years.

With the purpose of making legislation SME friendlier, the Commission has adjusted to some principles such as all products should scrutinize more effectively of their impact on SMEs, legislation should be different among small, medium and large
enterprises to sure that the administrative burden is proportional to these types of enterprises (European Commission, 2008).

Furthermore, in the case of late payments, the Commission in order to protect SME from them, discourages their payments and ensures that SME are paid immediately for all commercial transactions due to SME are vulnerable to them (European Commission, 2008).

SME cope with many problems due to laws, rules and practices. The Commission is trying to implement effective motives to improve the framework in which SMEs active. Reducing bureaucracy, access to finance and improving consultation of small business are some such motives. (European Commission, 2008).

4.3 The impact of Basel I, II and III on SMEs’ financing

As SMEs have a tight relationship with the banking system, all changes by laws and regulations concerning the banks, tend to influence SMEs as well. The most important regulation system concerning their relationship is the three Basel Accords.

The first one, Basel I (1998) was the first step in banking regulation which specified the minimum amount of equity that banks required to hold. This amount of equity is called regulatory capital and its purpose was to protect banks from several risks such as credit risk and help them absorb any losses that might have because of these risks. For credit risk, a bank was required to hold 8% of risk weighted assets, which were set by the Basel Committee and reflected the riskiness of certain SME types. Despite the advantages of the regulation for the banks, others weaknesses soon appeared such as the lack of SME’s risk sensitivity. Whether a SME was assumed to be of AAA* rating or down rated or closely to default, the risk weight remained the same for both firms. As a consequence, the Basel Committee started to work on the Basel II Accord in 1999 (Basel Committee on Banking Supervision, 2001).
The New Basel II Accord embodies the risk sensitivity factor in the calculation of credit risk capital requirement. The new concept regarding this Accord (1999) was that the banks were in the position to use their internal risk assessments in order to estimate on their own the regulatory capital requirements (Basel Committee on Banking Supervision, 2004).

Basel II helped a lot in the measurement of credit risk of SMEs. Many banks have created different quantitative credit risk measures for giving capital to the SMEs and make better their risk management. Those new measures lead to the implementation of higher fees and administrative costs on clients in order to enter the new capital regulations. Thus, the effort of SMEs to access external financing is now even more difficult due to a higher sensitivity for risks and profits in the finance sector. Business start-ups and SMEs, which want to introduce new markets, may suffer from shortages regarding finance (UEAPME, 2008).

Nowadays, Basel II is considered to be obsolete because these measures are not enough to response to problems revealed by the financial crisis. The new regulatory system, Basel III, will influence the relations between banks and SMEs (Ayadi, 2005). Basel III was created to increase the stability of banking sector. First, it enhances the quality and quantity of capital with a concentration on equity to absorb losses. Second, banks should keep capital for less liquid, credit sensitive assets with much longer holding periods. Finally, there will be stronger supervision, more risk management and standards (KPMG, 2011). The Basel III rules will have the impact on the beginning of 2013 and will be progressively phased in by 2019. Thus, SME will benefit by the new system as it ensures a more stable financing environment and provides easier rules when coming to gaining finance.
Chapter 5

Alternative evaluation approaches to default prediction

5.1 Introduction

The aim of this study is to identify the extent to which European banks lend the enterprises in the SME sector in Europe and to establish the methods adopted for lending to privately-owned SMEs. In specific, we employ the revised Z-Score approach for bank credit rating purposes developed by Altman (2000). In short, the purpose of our study is to analyse a bankruptcy classification model such as the Zeta (Z) Credit Risk Model. The latter will help us exam the creditworthiness of SMEs and classify defaulted companies up to five years prior to failure. The firm sample consists of manufacturers, retailer, wholesalers and other services.

This model is empirically derived from a database of pooled creditor data. This option may pose initial difficulties, as data must be collected on a standard annual basis, but will result in more powerful and accurate models. Because the original Altman Z-score model was being referred only to publicly traded companies and it is mainly for manufacturers, we test and the modified version of this model and its applicability in the corporate field. It is based on a profile of bankrupt and non-bankrupt manufacturers and can be applied to other private industrial firms as well.

For these private firms, we include specific financial indicators or ratios using data for the period 2006-2010 and we propose the revised Z-score model by Altman (2000) for privately-owned manufacturing companies. Using 5 financial ratios reflecting the firm’s profitability, leverage, liquidity and activity we attempt to evaluate default risk and predict enterprise’s failure.
The bank’s decision to grant loans to SMEs would depend on firm’s cash position, its future profits, its current liabilities to several creditors and its liquidation value. The combination of these five financial ratios as being specified in the Altman’s Z-score model (1968 & 2000) for SMEs is used to calculate the probability of firm’s default. The difference between the two models that we implement in this study (the Z-score model and the Z-score revised-model) is that the latter model uses the book value of equity for manufacturers, non-manufacturer industrials and emerging market credits whereas the original Z-score model makes use of the book value of equity only for the privately-owned firms. The market value of equity is used in Z-score model only for the publicly-owned firms listed in stock exchange. That’s why the Z-score revised-model is considered as a benchmark for measuring bankruptcy or defaulted risk of private SMEs.

5.2 Credit evaluation scoring models

Traditional methods have tried all these decades to estimate the probability of default (denoted PD), rather than the potential losses in the event of default (denoted LGD) of the small-medium sized enterprises. The three broad categories of traditional models used to estimate the default probability of SMEs are (Altman, 2002):

(1) Expert systems,
(2) Rating systems and
(3) Credit scoring models.

Almost all of the credit risk models that have been used in the past and continue to be in use nowadays involve the combination of some quantifiable financial ratios of firm performance with a number of variables that try to capture some qualitative elements of the credit process (Altman, 2002). The challenge that banks face in managing SME risks is to make an accurate risk assessment of a large number of SME loan applications without generating high costs per application. Therefore,
banks that work with large numbers of SMEs need to use automatic processes in making their credit decisions in order to minimize the costs of each lending decision. In recent years banks have adopted a new technology called credit scoring for small and medium enterprises. Credit scoring is an automated statistical method used to assess the risk of default of a credit applicant. It analyses financial historical data on borrowers to identifying certain characteristics that predict the likelihood of the borrower defaulting on his/her loan sometime in the future.

According to Peter (2007), credit scoring models are used internationally in the procession of credit products such as SME loans and their economic benefits are considered to be significant due to their:

- accuracy (if we use proven factors, our results can be highly accurate).
- speed (their automatism helps to faster and more efficient credit decisions).
- quantitative data (data gathered easily and several factors compared to specific measures and same groups, which provide us with more efficient evaluations for SMEs).
- effective portfolio management (loan defaults are predicted with high accuracy resulted in lower credit problem loans).

Using the results from the analysis of these models, banks can derive a score for evaluating the risk associated with each SME credit application. An implementation of the credit scoring model depends on data availability and cost considerations.

### 5.2.1. MDA (Multivariate Discriminant Analysis)

Altman introduced the multivariate approach in 1968 known as multivariate linear discriminant analysis (MDA) as an improvement in Beaver’s univariate model. MDA is a statistic technique procedure\(^7\) that is used in order to classify an observation into two or more groups with common characteristics and takes into consideration several

---

variables in the failure prediction of firms simultaneously (Slotemaker, 2008). It is mainly used in the classification of qualitative depended variables into defaulted or healthy firms. It is a linear combination of variables which provide us with the best discrimination between two groups or else a linear combination of ratios that best separate companies into bankrupt on non-bankrupt. It is preferable to logistic regression since it has more statistical power.\(^8\)

Altman’s goal via MDA method is the seeking of those independent variables which would contribute greatly in the model’s predictive ability without necessarily presents the highest statistic significance if they were examined separately. So, Altman’s objective goal is to find and use those index numbers which would offer the maximum lack of homogeneity between the two groups and the maximum homogeneity into the group of defaulted or non-defaulted firms separately. He made use of samples of different industry companies and significance tests (F value, T-test) in order to verify the significance of variables and test the contribution of the chosen variables to the discriminating power of its model. The complete discriminant model that had applied with the specific ratios taken into account led to Altman’s Z-score model.

The first step is to classify our firms into two groups, bankrupt and non-bankrupt. Afterwards, we gather the data (financial ratios) for the companies and try to construct a linear relation of these which best discriminates between the groups. If we use the same quantitative data and financial ratios for all the companies in our analysis then the MDA determines a set of discriminant coefficients and produces a Z-Score value to classify the firms as bankrupt or not. Once we have estimated the discriminant coefficients of our sample, we can find out the discriminant Z-score for each company and categorize the firm to bankrupt or non-bankrupt.

In the MDA model the following assumptions are made:

- The value of each ratio follow the normal distribution

\(^8\) MDA is based on two restrictive assumptions: 1) the independent variables included in the model are multivariate normally distributed; 2) the group dispersion matrices are equal across the failing and non-failing group. See Barnes(1982)
• The variance of the error term is constant across groups and independent of the variables in the model (no heteroscedasticity).

• The ratios are not highly correlated with each other

Finally, we conduct several tests that assess the contribution of each independent variable to our model. Each test displays the results for the independent variable using the grouping variable (i.e. the manufacture industry) as the factor that affects the Z-score of our model. If the significance value of probability is more than 0.005, the variable doesn’t play a significant role to our model. The smaller the results, the better the discriminating power of the variable are.

5.2.2 The Linear Probability Model

The Linear Probability Model was developed as an alternative method to Discriminant Analysis Model. It is considered as a special case of ordinary least squares (OLS) method. In this model, the dependent variable (Z) is binary. In our case (the prediction of firm’s bankruptcy), the Z variable takes the value of 1 if it continues to operate and the value of 0 if it goes bankrupt. We follow this procedure so as to indicate that the parameters that influence the Z-score can be different from the original ones for many reasons:

(1) parameters can’t be constant for different industry groups;

(2) the data that we use can be misleading to our estimations and

(3) the parameters of the initial Z-score model are estimated on the basis of default or non-default observations instead of using expectations.

According to the Z-score index obtained by a multiple discriminant analysis (MDA), the best predictors of failure are retained earnings/total assets, working capital/total assets, EBIT/total assets, book value of equity/book value of total debt and sales/total assets.
5.2.3 Logistic Regression Model

Historically, the logistic regression model\(^9\)(or logit) has been the most widely used method for constructing scoring systems for SME. We use this model, which is a suitable method of measuring individual credit risk, in order to predict the probability of whether an event can happen by fitting data to a logit function: its outcome is expressed as a measure of default probability (Bank of International Settlements, 2006). It is a linear model used for binomial regression. There are two models of logistic regression: binomial/binary and multinomial logistic regression.

The binomial method weighs the independent variables and assigns a score to each company. Independent variables are all potentially relevant parameters that try to capture the degree of information asymmetry. The logit equation takes the following form:

\[
\text{logit}(p) = \log [p (1 - p)] = \log(p) = a + BX + e,
\]

where \(p\) is the probability that a firm will go bankrupt; \(a\) is the coefficient estimate of intercept; \(B\) is a vector of coefficient estimate of the five financial ratios in the Z-Score model; \(X\) is the observed predictor variable values; and \(e\) is any random factor external to the model that is log-normally distributed by assumption. The dependent variable can take the value of 1 with a probability of bankruptcy \(p\) or the value 0 with probability of non-failure \(1-p\).

\(^9\)As an advantage of using the logistic regression, we are free from the multivariate assumption among independent variables.
5.2.4 Probit Regression Model

The probit model, which is based on the normal distribution, estimates the probability that \( Y=1 \) (a condition is fulfilled) given the value of the independent variable \( X \). The probit model is the same as the logit one, except that it is based on the cumulative normal distribution rather than the logistic distribution. Both of them estimate the probability of the outcome given the values of the independent variables used to explain that outcome. Here is what a cumulative normal distribution looks like:

\[
\Pr(y=1|x) = \Phi(x_b)
\]

where \( \Phi \) is the standard cumulative normal probability distribution and \( X_b \) is called the probit score or index. Since \( X_b \) has a normal distribution, interpreting probit coefficients requires thinking in the \( Z \) (normal quantile) metric. The interpretation of a probit coefficient, \( b \), is that a one-unit increase in the predictor leads to increasing the probit score by \( b \) standard deviations. The chief difference between logit and
probit analyses is that the normal or probit curve approaches the axes (i.e., the values of 0 or 1) more quickly than the logistic curve.

The log-likelihood function for probit is:

$$\ln L = \sum w_j \ln \Phi(x_j \hat{\beta}) + \sum w_j \ln \left(1 - \Phi(x_j \hat{\beta})\right)$$

where $w_j$ denotes optional weights.
Chapter 6

Hypotheses, variable selection and Altman tool model

6.1 Introduction

In this research we will try to classify a sample of 189 European SMEs in two classes, bankrupt or non-bankrupt and if the banks be in the position to proceed in granting loans to them. For our research’s purpose we employ a model that is based on companies’ financial ratios through a period of five years. In this case a multivariate discriminant analysis model such as the initial Altman’s Z-score model and its revised model is used to create a linear model by using 5 common financial ratios and analyzes the collected data which classifies the firms according to their financial data. (Slotemaker, 2008).

6.2 Description and selection of variables & ratios

All of the variables that we have used within the literature are financial ratios. The financial ratios, being mainly selected on a theoretical basis, are applied by almost all studies concerning the default prediction. The ratios that we have selected for the purpose of our empirical research are considered to be significant assessment factors of SMEs’ failure prediction, with low correlation between the variables and should represent the various relevant risk factors. These ratios, which are divided into five categories that measure, in general, the liquidity (working capital to total assets and current assets to current liabilities), solvency or leverage (total equity to total assets) and profitability (total debt to cash flow, net income to total equity) of companies, seemed to prevail as the most important indicators.
Table 3: Financial indicators in Altman’s Z-Score model and financial area

<table>
<thead>
<tr>
<th>Factor</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage</td>
<td>Retained earnings / Total Assets</td>
</tr>
<tr>
<td>Productivity</td>
<td>EBIT / Total Assets</td>
</tr>
<tr>
<td>Solvency</td>
<td>Book Value of Equity / Book Value Total Debt</td>
</tr>
<tr>
<td>Liquidity</td>
<td>Working Capital / Total Assets</td>
</tr>
<tr>
<td>Efficiency</td>
<td>Sales / Total Assets</td>
</tr>
</tbody>
</table>

The order of their significance is not always stated since different studies worldwide cite a different ratio as being the most effective indicator in predicting firm’s creditworthiness. The liquidity ratios determine whether the company can fulfill its short term obligations and the solvency ratios show us how the capital structure of firm is financed. Finally the profitability ratios reveal the ability of the company to make profits on its investments in order to improve its financial condition or to declare bankruptcy. These financial ratios are obtained from the financial data that we have gathered for all the selected European firms.

6.3 Variable Measurement and data consideration

According to previous studies, eight firm-specific financial ratios are examined in this study, which cover the financial leverage ratio, profitability and liquidity ratio. A variable has a different variation to each model that could influence the outcome. We presume in general that our financial ratios are normally distributed and positively skewed so as to implement the proper linear statistical techniques.

The only criteria employed when selecting our dataset was to obtain the best possible approximation to the industry distribution of the European economy. The objective was to create a sample that could be, as best as possible, representative of the European economy. For our empirical analysis we choose various industry sectors (manufacturing industries, growth industries etc.), where nearly half of the enterprises been picked are belonged to manufacturing industry.
6.4 Description of the tool model – Altman model (1968) & Altman Revised Z-Score (2000)

The Z-score model was first published in 1968 by Professor Edward Altman. The Z-score formula was developed to provide a more effective financial tool for credit analysis. The model is used to predict the probability if firm will go bankruptcy. It is widely utilized because it uses multiple variables to measure the financial health and credit worthiness of a borrower (Altman, 1968).

The Z-score model measures the financial health of a firm with a quantitative way. It is focus on actual financial information derived from operating performance of the firm. It is an effective tool that indicates if there is improvement or deterioration in financial condition. It is used by managers to increase capital and secure credit. Also, it helps them to mitigate business strategies with capital allocation and provide transparency of financial condition to lenders and equity capital providers. Consequently, the Z-score formula has the ability to show creditworthiness to bankers and the business model to investors (Altman, 1968).

From a list of 22 financial ratios, Altman concluded in picking five of them. The Z-score is calculated by multiplying each of those five financial ratio categories (liquidity, profitability, leverage, solvency and activity) by an appropriate coefficient and then summing the results. The ratios are chosen on the basis of their significance and their contribution to the depended variable, the correlation among these variables and their relevance to the study. These values are combined in order to produce a credit risk score that best discriminates between firms that default and those that do not. For the purpose of our study, our aim is to see if Altman’s Z-Score credit model\(^\text{10}\) is applicable to European SMEs as in US companies as well.

To calculate the Z-Score, the results of each of the five ratios are multiplied by a set factor (i.e., a coefficient developed by Altman). The results of this multiplication are

\(^{10}\) However, at that time, multivariate analyses were already used for consumer credit evaluations, see ALTMAN (1968, p.591)
then added together to determine a company’s Z-score. Higher the score, higher the chances are for the firm to continue to operate. It is a good idea to compare a company’s Z Scores over time to get a better idea as to how the company is doing.

Using AMADEUS (Bureau Van Dijk) database as our data source, 189 unlisted industrial companies in EU during 2006-2010 were selected. AMADEUS contains fiscal balance sheets and income statements of quoted firms. From all these data, the relevant ratios were constructed and used to calculate the Z-Score according to initial Altman model (1968) for each company data according to Equation 1 below:

\[ Z = 1.23X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \] (1)

The variables \( X_1, X_2, X_3, X_4 \) and \( X_5 \) that best discriminated bankrupt and non-bankrupt companies were:

- \( X_1 = \text{Working Capital (WC) to Total assets (TA)} \)
- \( X_2 = \text{Retained earnings (RE) to Total assets (TA)} \)
- \( X_3 = \text{Earnings Before Interest & Taxes (EBIT) to Total assets (TA)} \)
- \( X_4 = \text{Book Value of Equity (BVE) to Book Value of Total Liabilities (TL)} \)
- \( X_5 = \text{Sales (S) to Total assets (TA)} \)

\( Z \) = Overall Index or Score

where:

- Working Capital is equal to Current Assets minus Current Liabilities. This is a measure of liquidity. The WC/TA ratio is a measure of the net liquid assets of the firm relative to the total capitalization.
- Total Assets is the total of the Assets section of the Balance Sheet.

\[ \text{ALTMAN, E.I.},(2000), \text{Predicting financial distress of companies : Revisiting the Z score and ZETA Models} \]
• Retained Earnings is Net Profit minus dividends and is found in the Equity section of the Balance Sheet. This is a measure of the firm’s age and reports the total amount of reinvested earnings and/or losses of a firm from the time it was founded. We can say that RE/TA ratio measures the leverage of a firm.

• EBIT includes the income or loss from operations and from any unusual items but not the tax effects of these items. This is a measure of the firm’s productivity of assets by measuring how much return is being received from the assets.

• Book Value of Equity is the total of the Assets minus the total of the Liabilities (also known as Shareholder’s Equity)

• Book Value of Total Liabilities is the sum of all current and non-current liabilities from the Balance Sheet.

• Sales categorized as revenues in the firm’s Income statement. A standard capital-turnover ratio that provides information of a firm’s ability to generate revenue from the use of company assets.

A score of 2.99 or higher indicates that the firm is in good condition and there is not a threat of bankruptcy. But a score of 1.81 (Danger threshold cut-off) or below is a strong indicator that a probability of bankruptcy is more likely to happen. The area between the danger threshold cut-off and a Z-core of 2.99 is identified as zone of ignorance or “Grey zone”.

### 6.4.1 Variable selection, weightings and construction of the Revised Altman Z-score model

In 2000, Altman made an extension of his initial model which was only applicable to publicly manufacturing traded firms in order to include non-registered and non-manufacturing enterprises as well. But various questions were raised regarding the technique that was going to be used (Altman, 2002).
Which ratios play the most significant role in predicting bankruptcy problems?

How these selected ratios should be weighted into our model?

What should be the weight gravity for these ratios?

Altman has since developed two additional models: one for privately held manufacturing companies and another for non-manufacturing companies (sometimes called “general use companies”). To apply the model to non-public companies, he replaced the market value of equity for the book value of equity. He re-estimates his own initial model rather than changing these two variables and obtained the following “discriminant function” of Z-Score ($Z'$)\(^{12}\) to distinguish healthy companies from those with a high probability of bankruptcy:

**Revised Z-score for private manufacturing companies**

\[
Z_1 = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.42X_4 + 0.998X_5 \tag{2}
\]

The resulting Z-Scores from the above equation show the economic situation of a firm. A score of 2.9 or higher indicates that the firm is in good condition, there is not a threat of bankruptcy and insolvency in the two further years is less likely to happen. But a score of 1.23 (Danger threshold cut-off) or below is a strong indicator that further development cannot be specified more precisely and bankruptcy is likely. The area between the danger threshold cut-off and a Z-core of 2.9 is identified as zone of ignorance or “Grey zone”.\(^{13}\)

**6.4.2 A Further Revision – Model for Non-Manufacturing Firms**

In order to avoid the industry effect in the previous formula, which is more likely to appear when asset turnover included so as to adapt for non-manufacturing companies, Altman removed the fifth variable $X_5$ (Sales to Total Assets) of the function and


\(^{13}\) ALTMAN (1968). He assumes the existence of a middle interval that he depicts as “grey zone” (or “zone of ignorance” or “grey area”, see ibid, p.606)
changed the market value of equity in the variable $X_4$ with the book value of equity so the new Z-Score model for non-manufacturers ($Z_1$) took its final form\(^\text{14}\):

*Revised Z-score for privately owned non-manufacturing businesses*

$$Z_1 = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \ (3)$$

A score of 1.10\(^\text{15}\) or lower indicates that the firm is threatened by the serious financial problems in the next two or three years and bankruptcy is likely while a score of 2.60 or higher can be an indicator that bankruptcy is not likely. A score between the two is the grey area.

Once the values of the coefficient variables $X_1$ through $X_5$ are estimated, it is possible to calculate the score for each firm and then we can compare the profile of an individual firm with that of the alternative grouping. This Zeta credit risk model is considered to be the continuation of the original Z-Score approach (1968) with some extra adjustments. The reasons behind this can be traced to the fact that now the retailers can be analyzed on an equal basis with manufacturers and because this advanced model included the most recent changes in financial accounting practices (Altman, 2002).

\(^{14}\) ALTMAN, SAUNDERS (1998, p.1737f):“The Z-Score model is a four variable version of the Z-score approach. It was designed to reduce distortions in credit scores from different industries”

\(^{15}\) See ALTMAN (2002, p.22)
Chapter 7

Data Collection

7.1 Data sources and the construction of the dataset

This chapter describes the data we collected in order to perform the empirical part of our study and the sample set as well. From the financial viewpoint, a common definition of a firm's failure is insolvency, bankruptcy, or liquidation. The data used in this paper are extracted from the Amadeus-Bureau Van Dijk database, a database which includes financial information for millions registered firms in the whole Europe area and gives us the chance to study thoroughly the characteristics of each firm that belongs to SME sector across European countries.

The survey provides useful information about firm’s characteristics, their economic activity and financial condition that allow us to take into consideration several factors that might influence the demand for credit by firms and the capacity of banks to satisfy that demand. The Amadeus database includes all the firm accounting financial information –balance sheets, income statements, financial ratios– with their financial profiles giving details for their legal form, headquarters address, telephone, website, year of incorporation, number of employees, executive and senior managers, activity identification codes, trade description and so on.
7.2 Data Sample

We draw on data concerning firms’ financial conditions and the geographical distribution of them from a five-year survey (2006-2010) of about 189 European firms of specific sectors. For the purpose of this paper, our analysis concentrates on several European economies such as Italy, France, Germany, Greece, Sweden, Finland, Belgium etc. These firms belong to several industrial sectors (manufacture, services, retail, wholesale etc.), most if not all of them are considered as medium regarding their number of employees, annual turnover or sales and are mainly private enterprises neither public nor traded or listed in stock exchanges.

Table 4: Countries of origin and no of companies per country

<table>
<thead>
<tr>
<th>Countries</th>
<th>No of companies</th>
</tr>
</thead>
<tbody>
<tr>
<td>France</td>
<td>42</td>
</tr>
<tr>
<td>Italy</td>
<td>34</td>
</tr>
<tr>
<td>Greece</td>
<td>20</td>
</tr>
<tr>
<td>Belgium</td>
<td>12</td>
</tr>
<tr>
<td>Spain</td>
<td>20</td>
</tr>
<tr>
<td>Finland</td>
<td>4</td>
</tr>
<tr>
<td>Great Britain</td>
<td>6</td>
</tr>
<tr>
<td>Germany</td>
<td>5</td>
</tr>
<tr>
<td>Sweden</td>
<td>22</td>
</tr>
<tr>
<td>Portugal</td>
<td>15</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>2</td>
</tr>
<tr>
<td>Estonia</td>
<td>2</td>
</tr>
<tr>
<td>Netherlands</td>
<td>5</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>189</strong></td>
</tr>
</tbody>
</table>
Table 5: SME trade segmentation (Industry and Number)

<table>
<thead>
<tr>
<th>Industries</th>
<th>Number of Companies</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Retail</td>
<td>28</td>
</tr>
<tr>
<td>2. Manufacture of beverage and food</td>
<td>31</td>
</tr>
<tr>
<td>3. Wholesale</td>
<td>29</td>
</tr>
<tr>
<td>4. Computer programming consultancy &amp; related activities</td>
<td>27</td>
</tr>
<tr>
<td>5. Administrative, Rental &amp; Lease activities</td>
<td>24</td>
</tr>
<tr>
<td>6. Real Estate</td>
<td>22</td>
</tr>
<tr>
<td>7. Repair &amp; Installation</td>
<td>28</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>189</strong></td>
</tr>
</tbody>
</table>

As we have told before, our AMADEUS survey data cover 189 firms from a very large range of financial privately owned companies setting specific criteria (for reasons of data processing capacity, we only select those firms that had at least 50 or more employees and annual operating revenues nearly to 10 million euros (€) in the final year available, all from the European area, belonging to small or medium legal-type category and mainly private-owned). All our firms contain the basic financial data (i.e. turnover, total assets, total liabilities, net income, shareholders funds, cash flow etc.) and we employ firm characteristic data to predict the probability of corporate default of these unlisted firms.

7.3 Financial condition of SMEs

The tables below give the number of SMEs of seven different sectors and the three levels of their financial health as ii is calculated through the initial Altman z-score model (1968) and its revised model (2000) that we have described above (the results can be seen more thoroughly in the excel spreadsheets).
Table 6: Level of financial health of enterprises (Altman 1968 model)

<table>
<thead>
<tr>
<th>Industries</th>
<th>Healthy</th>
<th>Grey Zone</th>
<th>Unhealthy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Retail</td>
<td>12</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>2. Manufacture of beverage and food</td>
<td>6</td>
<td>11</td>
<td>14</td>
</tr>
<tr>
<td>3. Wholesale</td>
<td>9</td>
<td>19</td>
<td>1</td>
</tr>
<tr>
<td>4. Computer programming consultancy &amp; related activities</td>
<td>16</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>5. Rental &amp; Lease activities</td>
<td>7</td>
<td>11</td>
<td>6</td>
</tr>
<tr>
<td>6. Repair &amp; installation of machinery and equipment</td>
<td>10</td>
<td>14</td>
<td>4</td>
</tr>
<tr>
<td>7. Real estate activities</td>
<td>6</td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td><strong>Total No</strong></td>
<td><strong>66</strong></td>
<td><strong>81</strong></td>
<td><strong>42</strong></td>
</tr>
<tr>
<td><strong>%</strong></td>
<td><strong>34.92</strong></td>
<td><strong>42.85</strong></td>
<td><strong>22.22</strong></td>
</tr>
</tbody>
</table>

Table 7: Level of financial health of enterprises (Altman revised 2000 model)

<table>
<thead>
<tr>
<th>Industries</th>
<th>Healthy</th>
<th>Grey Zone</th>
<th>Unhealthy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Retail</td>
<td>12</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>2. Manufacture of beverage and food</td>
<td>6</td>
<td>15</td>
<td>10</td>
</tr>
<tr>
<td>3. Wholesale</td>
<td>22</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>4. Computer programming consultancy &amp; related activities</td>
<td>22</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>5. Rental &amp; Lease activities</td>
<td>10</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>6. Repair &amp; installation of machinery and equipment</td>
<td>25</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>7. Real estate activities</td>
<td>7</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td><strong>Total No</strong></td>
<td><strong>104</strong></td>
<td><strong>52</strong></td>
<td><strong>33</strong></td>
</tr>
<tr>
<td><strong>%</strong></td>
<td><strong>55.02</strong></td>
<td><strong>27.51</strong></td>
<td><strong>17.46</strong></td>
</tr>
</tbody>
</table>
From the above tables we can see that both models more or less produce the same results as far as the number of defaulted firms (22.22% and 17.46% respectively) but the percentage of non-defaulted SMEs is greater than that of the initial Altman model (55.02% versus 34.92%). Major deviations in the results between the two models concerning the healthy companies and unhealthy ones are produced in the case of firms which are engaged in the repair-installation and wholesale sector.
Chapter 8

Methodology approach and Empirical Results

8.1 NLME model and data analysis

By far the most common application of NLME (Non-Linear Mixed Effects) models is for repeated measures data, in particular, longitudinal data. The nonlinear mixed-effects model for repeated measures proposed by Lindstrom and Bates (1990) can be thought of as a hierarchical model. At one level the jth observation on the ith group is modeled as:

\[ y_{ij} = f(\phi_{ij}, v_{ij}) + \epsilon_{ij}, \quad i = 1, \ldots, M, \quad j = 1, \ldots, n_i, \]

where:

- \( M \) is the number of groups, \( n_i \) is the number of observations on the ith group, \( f \) is a general, real-valued, differentiable function of a group specific parameter vector \( \phi_{ij} \) and a covariate vector \( v_{ij} \), and \( \epsilon_{ij} \) is a normally distributed within-group error term.
- The function \( f \) is nonlinear in at least one component of the group-specific parameter vector \( \phi_{ij} \), which is modeled as \( \phi_{ij} = A_{ij}\beta + B_{ij}bi, \) \( bi \sim N(0,\Psi) \). \( \beta \) is a \( p \)-dimensional vector of fixed effects and \( bi \) is a \( q \)-dimensional random effects vector associated with the ith group (not varying with \( j \)) with variance–covariance matrix \( \Psi \). The matrices \( A_{ij} \) and \( B_{ij} \) are of appropriate dimensions and depend on the group and possibly on the values of some covariates at the jth observation. This model is a slight generalization of that described in Lindstrom and Bates (1990) in that \( A_{ij} \) and \( B_{ij} \) can depend on \( j \). This generalization allows the incorporation of “time-varying” covariates in the fixed effects or the random effects for the model.
It is assumed that observations corresponding to different groups are independent and that the within-group errors $ij$ are independently distributed as $N(0, \sigma^2)$ and independent of the $bi$. The assumption of independence and homoscedasticity for the within-group errors can be relaxed. Because $f$ can be any nonlinear function of $\phi_{ij}$, the representation of the group-specific coefficients $\phi_{ij}$ could be chosen so that $A_{ij}$ and $B_{ij}$ are always simple incidence matrices. However, it is desirable to encapsulate as much modelling of the $\phi_{ij}$ as possible in this second stage, as this simplifies the calculation of the derivatives of the model function with respect to $\beta$ and $bi$, used in the optimization algorithm. In a call to `nlme` the arguments fixed and random are used to specify the $A_{ij}$ and $B_{ij}$ matrices, respectively.

We employ panel regression using a sample of 189 SMEs from several European countries to examine how the Z-score value is influenced by changes in the independent variables ($X_1$, $X_2$ etc.) and the impact of each industrial sector to it.

By employing the logistic regression we re-examine the significance of the five financial ratios that we have used in Altman’s model as well as the joint significance of the cross-section effects and the period effects separately. In other words, we assess the importance of efficiency in predicting firm defaults over and above of that explained by financial factors. The advantage of applying the technique of logistic regression is that our empirical results are theoretically more accurate even if $X$ is not normally distributed. The likelihood ratio test helps us to evaluate the whole model as well as the individual independent coefficients by testing if the factors have a significant influence on our dependent variable, the Z-score value in our case.

The methodology model of logistic regression can be phrased in terms of Z-score as follows:

$$Z_{it} = \frac{e^{A_0 + A_1X_{1it} + A_2X_{2it} + A_3X_{3it} + A_4X_{4it} + A_5X_{5it}}}{1 + e^{A_0 + A_1X_{1it} + A_2X_{2it} + A_3X_{3it} + A_4X_{4it} + A_5X_{5it}}} + U_{it}$$
where:

\[ X_i = b_0 + b_1 x_1 + \ldots + b_p x_p + e_i \]

where:
- \( X_i \) is the dependent variable (e.g. a leverage ratio)
- \( b_0 \) is the estimate of intercept
- \( b_j \) is the coefficient estimate of five financial ratios in the Z-score model
- \( p \) is the number of predictors (ratios)
- \( e_i \) is the error in the observed value

In a matrix form the above equation can be easily rewritten as:

\[
\begin{align*}
\mathbf{Z}_{it} &= e^{\mathbf{X}_{it} \mathbf{b}} / (1 + e^{\mathbf{X}_{it} \mathbf{b}}) + \mathbf{u}_{it} \\
\end{align*}
\]

Where the transpose matrix \((X')\) is referred to the variables \((X_1-X_5)\) and \(b\) is a vector which includes all parameters which be estimated. The main estimation method which is applied to get values for coefficients of the non-linear regression is non-linear least squares, using the Newton-Raphson algorithm. The structure of our data is a balanced panel, due to the fact that there are no missing values so the number of observations which will be used to estimate is equal to the number of individuals under examination multiplied by the number of the available years. In our case the total observations of a pooled sample (there is no distinction between individuals) will be \(189*5 = 945\) observations.

### 8.2 Interpretation of findings

Probit model, as we have told before, is an extension of the logit model, as they are both generated by binomial family. There is a number of observations though, beyond which binomial distribution converges to normal distribution, according to central limiting theorem (CLT). To begin with our analysis we should see descriptive statistics for each variable separately, treating them initially as a pooled sample and
then for each individual. In our research we employ probit regression model, due to the fact that the dependent variable (Zit) is expressed as 1 if Z-score is below 1, thus it is more probable for a firm to undergo bankruptcy, while 0 if Z-score is above 1. So having as “success” the value of Z-score below 1 and “failure” the value of Z-score above 1, our analysis is fully described by a probit model. Furthermore, research on this field has historically been conducted by applying a probit model analysis (Carbo-Valverde S. et al (2005), Vougaris F. et al (2000)) and in some cases by applying a logit model (Hardle W. et al (2009)).

We examine 5 variables that are believed to determine their effect on z-score value (Table 8).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sample Size</th>
<th>Minimum</th>
<th>First Quartile</th>
<th>Median</th>
<th>Mean</th>
<th>Third Quartile</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>945</td>
<td>-0.3877</td>
<td>0.1480</td>
<td>0.2555</td>
<td>0.274</td>
<td>0.3912</td>
<td>0.9175</td>
</tr>
<tr>
<td>X2</td>
<td>945</td>
<td>-0.571</td>
<td>-0.002</td>
<td>0.030</td>
<td>0.0719</td>
<td>0.1139</td>
<td>3.308</td>
</tr>
<tr>
<td>X3</td>
<td>945</td>
<td>-0.5580</td>
<td>0.0019</td>
<td>0.04616</td>
<td>0.0466</td>
<td>0.111</td>
<td>0.5905</td>
</tr>
<tr>
<td>X4</td>
<td>945</td>
<td>-0.7155</td>
<td>0.2348</td>
<td>0.5126</td>
<td>0.9799</td>
<td>1.075</td>
<td>34.0179</td>
</tr>
<tr>
<td>X5</td>
<td>945</td>
<td>0</td>
<td>1.007</td>
<td>1.407</td>
<td>1.541</td>
<td>1.886</td>
<td>5.127</td>
</tr>
</tbody>
</table>

From the table we can see that variable X1, X2 and X4 are heavily skewed, due to the fact that median and mean are not equal, while X3 and X5 can be considered to be normally distributed. The variables X4 and X5 are by significantly higher compared to the other variables because they have greater means (0.9799 and 1.541 respectively). This means that the above variables are linked to the performance evaluation of firms through z-scores. The representation of results to a table does not always help to make clear and important generalizations. That is why we create box – plots for each variable as well as histograms adapted with normal line.
We check the normality of the error term so that the differences between the observed and model-predicted values of the dependent variable do not affect negatively our model. The histogram of the residuals will help us check the assumption of normality of the error term.

Diagram 1: Boxplot for the variable $X_1$

The distribution of $X_1$ variable is heavily right skewed and we can see that there are some outliers in the upper whisker.

Diagram 2: Boxplot for the variable $X_2$

The same thing happens in the distribution of variable $X_2$. The maximum value of the outlier is above 3 while the majority of $X_2$’s values move near zero.
Diagram 3: Boxplot for the variable $X_3$

The distribution of $X_3$ is quite normal as there are outliers but they are equally distributed left and right of its mode.

Diagram 4: Boxplot for the variable $X_4$

The distribution of $X_4$ seems also to be heavily right skewed as there are many outliers above right whisker. It is certainly not normal.
The distribution of $X_5$ is right skewed as the same happens as in the case of $X_4$ there are many outliers righter than the right whisker.

Having examined the descriptive statistics for each variable separately, we may wish to test for existence of multicolinearity, simply by calculating the correlations between variables $X_1$ to $X_5$ with the use of a linear regression model.\textsuperscript{16}

<table>
<thead>
<tr>
<th></th>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>$X_4$</th>
<th>$X_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$X_2$</td>
<td>0.1311***</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$X_3$</td>
<td>0.2522***</td>
<td>0.4355***</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$X_4$</td>
<td>0.0267</td>
<td>-0.00088</td>
<td>0.0789*</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>$X_5$</td>
<td>0.1443***</td>
<td>0.141165***</td>
<td>0.08979**</td>
<td>-0.15824***</td>
<td>1</td>
</tr>
</tbody>
</table>

---

\textsuperscript{16} For the overall analysis that will follow, we used the statistical NLME model

In the Multiple Regression Analysis, colinearity problems emerged that suggest that the results may not be totally trustable. The sign of the coefficients explains the...
relationship between the selected variable and the default probability. All correlation coefficients are low enough and hence we can conclude that there is no problem of multicolinearity in the model, which does not allow the model to be estimated and in some cases, and if model is estimated indeed, values of coefficients and standard errors are found to be inconsistent and biased leading to false results as far as confidence of intervals and significant test are concerned. Specifically, as indicated by the very low p-values, correlation coefficients which are significant and positive are for the pairs \(X_1 - X_2, X_1 - X_3, X_1 - X_5, X_2 - X_3, X_2 - X_5, X_3 - X_5\) while negative are for the pair \(X_4 - X_5\). Uncorrelated must be considered the pairs \(X_1\) and \(X_4\) as well as \(X_2\) and \(X_5\). Furthermore, firms with higher working capital ratio as well as retained earnings and earnings ratio tend to be significantly more stable and have lower risk.

Having finished with the pivot statistics of each variable, we will proceed to the estimation of a probit model on a pooled data sample, using as starting values the coefficients of the linear model. Despite the difficulties a pooled data scoring model may have, as data have to be collected on a common basis, the results that we obtain will be more accurate. Multiple Linear Regression is used to model the value of a dependent variable based on its linear relationship to the predictors. In the following lines we will examine which predictors influence the most our dependent variable. The results of the pooled probit model are as shown in the table below:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Standard Error</th>
<th>T value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A_0)</td>
<td>0.98965</td>
<td>0.021042</td>
<td>47.0305***</td>
</tr>
<tr>
<td>(A_1)</td>
<td>7.0951</td>
<td>1.10136</td>
<td>6.44216***</td>
</tr>
<tr>
<td>(A_2)</td>
<td>38.333</td>
<td>7.77827</td>
<td>4.92822***</td>
</tr>
<tr>
<td>(A_3)</td>
<td>-22.788</td>
<td>6.92219</td>
<td>-3.29060***</td>
</tr>
<tr>
<td>(A_4)</td>
<td>0.38907</td>
<td>0.19986</td>
<td>1.946740**</td>
</tr>
<tr>
<td>(A_5)</td>
<td>0.0184</td>
<td>0.0993264</td>
<td>0.185374</td>
</tr>
</tbody>
</table>

**Sum of Squares** 37.55147

**Nagelkerke \(R^2\)(%)** 55.06

**F** 100.6865

**p-value (F)** 0.000
The alpha coefficient (A₀, A₁ etc.) is the most generally used reliability measure. A coefficient of at least 0.70 is considered reliable and alpha score greater than 0.8 indicates strong consistency among the items in each factor. From the table above, we can see that parameters A₀ to A₃ are statistically significant in less than 0.01 significance level (T-value); A₄ is statistically significant in less than 5% level of significance while A₅ is not statistically significant. X₁ affects positively the probability for a firm to declare bankruptcy and an increase by one unit contributes \( e^{7.0951}/(1+ e^{7.0951}) \) units to the probability of default, X₂ affects also positively and contributes \( e^{38.333}/(1+ e^{38.333}) \) and the same happens for all statistical significant variables. The sum of squares of residuals is 37.55, the coefficient of determination (pseudo r-square of Nagelkerke) is satisfying as it is 55% which means that 55% of firm’s bankruptcy probability is explained by the model and the regression is statistical significant as the value of F criterion is way above critical value of F distribution and the significance is less than 1%.

The pseudo r – squared of Nagelkerke is a measure of good fit in the case of a probit model. The corresponding measure in the case of a simple linear is the coefficient of determination or else known as r – squared which is the division of regression sum of squares to total sum of squares. On the other hand pseudo r- squared of Nagelkerke is given below:

\[
R^2 = 1 - \left[ \frac{L(0)}{L(\hat{\theta})} \right]^{2/n}
\]

where the numerator is the value of likelihood function of a probit model which is estimated using only the intercept, which is known as the null model, the denominator is the value of likelihood function of the full model and the exponent is the sample size. Like r-squared, Nagelkerke’s pseudo r – squared can move in the close interval from 0 to 1. Unlike simple linear regression, we can be satisfied if the value of the index above is above 30%, due to the fact that is a measure of good fit of non – linear regressions.
At this point it is crucial that we choose between the probit estimated model using a pool sample and a probit model with random or fixed effect, simply by applying a Hausman test.

Table 11: Results of the estimation of a panel structure probit model with fixed effects

<table>
<thead>
<tr>
<th>Parameter (Fixed Effects)</th>
<th>Value</th>
<th>Standard Error</th>
<th>T value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( A_0 )</td>
<td>1.5754</td>
<td>0.107</td>
<td>14.72</td>
<td>0.000</td>
</tr>
<tr>
<td>( A_1 )</td>
<td>0.7655</td>
<td>0.366</td>
<td>2.085</td>
<td>0.0376</td>
</tr>
<tr>
<td>( A_2 )</td>
<td>0.278236</td>
<td>0.21198</td>
<td>1.312</td>
<td>0.1901</td>
</tr>
<tr>
<td>( A_3 )</td>
<td>0.702223</td>
<td>0.43930</td>
<td>1.598</td>
<td>0.1107</td>
</tr>
<tr>
<td>( A_4 )</td>
<td>0.016738</td>
<td>0.02206</td>
<td>0.758</td>
<td>0.4485</td>
</tr>
<tr>
<td>( A_5 )</td>
<td>-0.124061</td>
<td>0.0649</td>
<td>-1.908</td>
<td>0.0570</td>
</tr>
<tr>
<td>Sum of Squares</td>
<td>130.4452</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nagelkerke - R^2(%)</td>
<td>50.87</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>85.099</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value (F)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In the table above we can see the results from the estimation of a fixed effect panel data probit model. The constant term is statistical significant as well as the coefficient of \( X_1 \) and \( X_5 \). All other coefficients are not statistically significant, as p – values are above 10% level of significance. The pseudo r square of Nagelkerke is very satisfying and the regression is statistically significant as p – value of F criterion (0.000) is less than 1% level of significance. The significance value (p-value) reflects the percentage or the probability that the results are due to change. A p-value of ≤0.01 is acceptable. In our case where p-value (F) = 0 we can claim that the relationship is truly significant.
Table 12: Results of the estimation of a panel structure probit model with random effects

<table>
<thead>
<tr>
<th>Parameter (Fixed Effects)</th>
<th>Value</th>
<th>Standard Error</th>
<th>T value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A0</td>
<td>-0.505</td>
<td>0.03604</td>
<td>14.02</td>
<td>0.000</td>
</tr>
<tr>
<td>A1</td>
<td>-7.8354</td>
<td>3.21414</td>
<td>-2.43782</td>
<td>0.0152</td>
</tr>
<tr>
<td>A2</td>
<td>-5.598</td>
<td>12.07320</td>
<td>-0.46371</td>
<td>0.6431</td>
</tr>
<tr>
<td>A3</td>
<td>4.5519</td>
<td>12.87193</td>
<td>0.35364</td>
<td>0.7238</td>
</tr>
<tr>
<td>A4</td>
<td>5.0405</td>
<td>1.96208</td>
<td>2.569</td>
<td>0.0106</td>
</tr>
<tr>
<td>A5</td>
<td>0.1248</td>
<td>0.44262</td>
<td>0.28197</td>
<td>0.7781</td>
</tr>
</tbody>
</table>

| Sum of Squares            | 1440.265 |

| Nagelkerke R²(%)          | 20.66    |
| F                         | 0.2568   |
| p-value (F)               | 0.890    |

Random effects estimation seems to be statistically insignificant, thus Hausman test is unnecessary to be implemented. Constant term, parameter of variable X1 and parameter of variable X4 are statistically significant, r-square of Nagelkerke is approximately 21%, which is relatively low compared to the same using fixed effects. Although not significant we can see graphically how most random effects’ terms are distributed among each firm. Note that in our research, we have engaged 189 European firms from all fields of economy (i.e retail, wholesale, services).

Another interesting thing to investigate is the fact that firms which belong to the manufacturing industry, tend to declare bankruptcy than firms which belong to other industry (i.e. retail, wholesale, services). In order to test for the industry effect on overall z-score or else, to test whether the regression model describes accurately the dependent variable for different groups, we will incorporate a dummy variable in logit model, which we will estimate using a pool sample and not a panel structure dataset, whose values are 1 if a firm is a part of one industry group (e.g. manufacturing firms) and 0 for all the other groups. The use of a pool instead of a panel data frame is done primarily due to the fact that we indirectly split the data set into two groups. Therefore
it is meaningless to make a further distinction between corporate and industries they belong to. Through the logistic regression analysis, we try to explore the relationship between firm’s z-score and the explanatory variables (X₁, X₂, etc.). Using the logistic regression coefficients (A₀, A₁, etc.) we will be able to estimate odds ratios for each of the explanatory variable in the model. Our model after the introduction of the dummies is as follows:

\[ Z_i = \frac{e^{A_0 + A_1 X_1 + A_2 X_2 + A_3 X_3 + A_4 X_4 + A_5 X_5 + A_6 X_6 + A_7 X_7 + A_8 X_8}}{1 + e^{A_0 + A_1 X_1 + A_2 X_2 + A_3 X_3 + A_4 X_4 + A_5 X_5 + A_6 X_6 + A_7 X_7 + A_8 X_8}} + u_i \]

As we can see from the algebraic expression of the model, there is no possibility dummy to be introduced to all variables of the model, due to the fact that the matrix of independent variables (X’X) becomes singular and this is ought to heavy multicollinearity. The results of the estimation are given at the following table:

Table 13: Estimated parameters of a logit model with dummy variable

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Standard Error</th>
<th>T value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A₀</td>
<td>0.978</td>
<td>0.0166</td>
<td>58.89</td>
<td>0.000</td>
</tr>
<tr>
<td>A₁</td>
<td>5.499</td>
<td>1.015</td>
<td>5.41</td>
<td>0.004</td>
</tr>
<tr>
<td>A₂</td>
<td>49.199</td>
<td>9.239</td>
<td>5.32</td>
<td>0.005</td>
</tr>
<tr>
<td>A₃</td>
<td>-25.832</td>
<td>9.239</td>
<td>-3.21</td>
<td>0.037</td>
</tr>
<tr>
<td>A₄</td>
<td>0.4781</td>
<td>8.029</td>
<td>2.13</td>
<td>0.045</td>
</tr>
<tr>
<td>A₅</td>
<td>0.221</td>
<td>0.224</td>
<td>1.81</td>
<td>0.058</td>
</tr>
<tr>
<td>A₆</td>
<td>35.135</td>
<td>0.121</td>
<td>2.30</td>
<td>0.049</td>
</tr>
<tr>
<td>A₇</td>
<td>91.794</td>
<td>15.276</td>
<td>1.49</td>
<td>0.116</td>
</tr>
<tr>
<td>A₈</td>
<td>-75.139</td>
<td>61.605</td>
<td>-1.54</td>
<td>0.109</td>
</tr>
<tr>
<td>A₉</td>
<td>-2.479</td>
<td>0.937</td>
<td>-2.64</td>
<td>0.041</td>
</tr>
<tr>
<td>Sum of Squares</td>
<td></td>
<td></td>
<td>34.175</td>
<td></td>
</tr>
</tbody>
</table>

Nagelkerke R²(%) 39.199

F 60.217

p-value (F) 0.000
The parameters of $A_6$ to $A_9$ are added to $X_1$, $X_2$ and $X_4$ respectively if dummy’s value is 1, which is interpreted that the firm belongs to manufacturing industry, while model is identical to the very first estimated model if dummy’s value is 0. From the table we can see that parameters $A_0$ to $A_5$ are statistically significant ($p$-value < 0.05). From the parameters of dummies $A_6$ and $A_9$ are statistically significant, which means that if dummy is 1 then on the slope of variable $X_1$ the value of 35.135 will be added, while on the value of the slope it will be added the value of -2.479. This means that manufacturing industry has an effect on the probability of a firm declaring bankruptcy and specifically variables $X_1$ and $X_4$ are the ones which are affected most. The value of residual sum of squares is 34.175, Nagelkerke’s R-square is high enough reaching almost 40% and the regression is statistically significant ($p$-value < 0.01).

Finally it would be also interesting to investigate which is the joint effect of the rest industries which we examine on the probability of a firm to default. For this reason we have created another dummy variable, which is complementary of the previous one and is 1 whenever belongs to an industry different from the manufacturing and 0 if belongs to the manufacturing industry. Introducing dummies to the variables $X_1$ to $X_5$ we have a double effect: 1) the indirect effect stems from how the industry affects the variable in which we introduce the dummy and 2) the direct effect which is how the industries affect the probability a firm is bankrupted. Various sets of models have been tested, mainly because of the fact that introducing dummies to all independent variables it is impossible for the model to be estimated as the matrix of independent variables is singular and the inverse of it cannot be computed. So we have resulted in the following model which captures the joint effect of non-manufacturing industries on the probability for a firm to default through the variables $X_1$ and $X_3$. The results of the estimation are given in the table below.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Standard Error</th>
<th>T value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_0$</td>
<td>0.988</td>
<td>0.020</td>
<td>47.106</td>
<td>0.000</td>
</tr>
<tr>
<td>$A_1$</td>
<td>7.355</td>
<td>1.204</td>
<td>6.105</td>
<td>0.003</td>
</tr>
<tr>
<td>$A_2$</td>
<td>38.310</td>
<td>7.841</td>
<td>4.885</td>
<td>0.005</td>
</tr>
<tr>
<td>$A_3$</td>
<td>-22.177</td>
<td>7.083</td>
<td>-3.130</td>
<td>0.037</td>
</tr>
<tr>
<td>$A_4$</td>
<td>0.387</td>
<td>0.201</td>
<td>1.918</td>
<td>0.057</td>
</tr>
<tr>
<td>$A_5$</td>
<td>0.0129</td>
<td>0.0099</td>
<td>0.130</td>
<td>0.345</td>
</tr>
<tr>
<td>$A_6$</td>
<td>-0.4913</td>
<td>1.163</td>
<td>-0.422</td>
<td>0.567</td>
</tr>
<tr>
<td>$A_7$</td>
<td>-1.634</td>
<td>3.736</td>
<td>0.437</td>
<td>0.557</td>
</tr>
</tbody>
</table>

| ESS       | 37.527 |
| Nagelkerke R² (%) | 55.167 |
| F         | 75.524 |
| p-value (F) | 0.000 |

From the table above our main remarkable notice is that the non – manufacturing industries do not affect the probability for a firm to default. The parameters $A_6$ and $A_7$ are referred to the dummies introduced to the variables $X_1$ and $X_3$ respectively. As we can see they are not statistical significant (p-value > 0.1) and so are the parameters of variables $X_5$ (p – value > 0.1) and $X_4$ (p – value > 0.05). The model, in a nutshell, satisfies several other criteria such as the statistical significance of all parameters simultaneously (p – value of F criterion < 0.01) and a relatively high value of Nagelkerke’s pseudo r- squared which exceeds 55%.
We can see that less than half of the firms contribute negatively to the probability of bankruptcy. There is a small group of firms, which is created in the left down corner of the diagram and we assume that they are firms which they come from developed western European countries and as it seems they have very little probability of being bankrupted. On the other hand a large group of approximately 40 firms move above zero and they are more susceptible to bankruptcy.
Chapter 9

Conclusions and limitations

Today’s business world is more competitive and risky than ever. The need for capital is the most common subject in business meetings. In this survey, we tried to approach a very important sector of the economy, the SMEs. This type of enterprises consist the basis of most countries’ economy, thus the effective use of sources of finance is a matter crucial for a country’s welfare and progress. Even if nowadays there are plenty of sources of finance for firms worldwide, small and medium enterprises (SME) have to carefully examine their choices when deciding on how to be funded.

The main result from this research is that a rating scoring model for privately-held corporate firms with few data requirements can be built. This fact led to the development of many models for predicting a firm’s possibility to go bankrupt within some time. Bankruptcy prediction is a matter that constantly concerns SME and countries, and thus models that were developed during the 1960s or 1970s are applied even today. The SME’s rating model according to their creditworthiness by the banks lead to the assessment of credit dangers under specific criteria and principles. Our aim was to see how specific statistical models as part of the bank’s credit decision making for the prediction of company default could effectively classify enterprises of diverse size, operating in different geographical areas and in different business sectors. The score methods allow an overall assessment of the risk of bankruptcy for the enterprises, based on a set of financial ratios that are affected by the degradation of the financial position. It is confirmed that if SE financial statements are to be used to predict credit risk, then some caution must be exercised in applying statistical methods and in interpreting results. The findings of our study demonstrate how important is for the banks to apply such models in order to manage their credit risk.
Through the proper transformation of our data and the implementation of econometric models, we manage to include economic factors in the analysis. Our scope was to examine the role of certain financial ratios in firms’ financial health (in terms of z-score measurement). Our results have shown that working capital ratio ($X_1$), retained earnings ratio ($X_2$) and EBITDA ratio ($X_3$) are useful and important ex-ante predictors of firm default and have a positive and significant effect on the default probability. Moreover, retained earnings/total assets appeared to be the most reliable predictor of failure.

While this research contributes to the knowledge on credit evaluation performance in the European banking sector we recognize certain limitations. Firstly, our sample is relatively small and restricted and does not permit catholic acceptance of the results of the present study to the whole European banking sector. Secondly, we should keep in mind that financial information is sometimes quite limited for a large part of SMEs. The update of this information would allow financial institutions to correct any misspecifications that might appear towards them. In conclusion, financial ratios are an important component in banks’ credit evaluation methods.
Bibliography


**Websites**


