"Three Essays on SMEs Credit Risk and Capital Structure"

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BY

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List of Acronyms

Abbreviation	Acronym
SME	Small and Medium-Enterprise
EIU	Economist Intelligence Unit
SBE	Small Business Entrepreneurship council
BLS	Bureau of Labour Statistics
SBA	Small Business Administration
IFC	International Finance Corporation
ANR	Artificial Neural Networks
BNN	Propagation Neural Network
SVM	Support Vector Machines
WNN	Wavelet Neural Network
RPA	Recursive Partitioning Algorithm
GA	Genetic Algorithms
CCB	Contingent Claims-Based
BSM	Black-Scholes-Merton Model
ROC	Receiver Operating Characteristic
BCBS	Basel Committee on Banking Supervision
LGD	Loss Given Default
EAD	Exposure At Default
M&M Theory	Modigliani and Miller Theory

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Dedication

To my parents and wife.

Abstract

The main purpose of this study is to provide further insight into the SMEs' credit risk and capital structure. Thus, this thesis presents three essays on SMEs probability of bankruptcy and capital structure in chapter 3 to chapter 5. The first empirical chapter investigates the extent to which size affects the SMEs probabilities of bankruptcy. I use a dataset of (11,117) US non-financial firms, of which (465) filed for insolvency under chapters 7/11 between 1980 and 2013. I forecast the bankruptcy probabilities by developing four discrete-time duration-dependant hazard models for SMEs, Micro, Small, and Medium firms. A comparison of the default prediction models for medium firms and SMEs suggest that an almost identical set of explanatory variables affect the default probabilities leading us to believe that treating each of these groups separately has no material impact on the decision making process. However, comparisons of the micro and small firms with the SMEs firms strongly suggest that they need to be considered separately when modelling credit risk for them.

The second empirical chapter investigates the reasons for SMEs' choice of being debt-free in their capital structure. Furthermore, I study to what extent different SME size segments (namely micro, small, and medium) affect the debt-free decision. I use a dataset of 95,450 firm-year observations of which there are 18,764 debt-free firm-year observations. I find that borrowing constraints and financing activities play a significant role in the debt-free capital structure decisions of the SMEs. A surprising result is that a large number of debt-free SMEs pay significantly higher dividends than their counterparts with debt. Finally, I find that pension obligations, and lease commitments do not play a significant role in explaining the debt-free policy. However, when conducting the logit regressions on entry and exit decisions of the debt-free SMEs I find that the NDTS plays a significant role in explaining the firm's decision whether to enter or exit the debt-free status.

According to the capital structure hypothesis, if firms deviate too far from their optimum capital structure they will not maximize their value. However, an increasing number of firms across different countries follow a debt-free policy, preferring to have no leverage compared to that which would maximize the firm value. In line with the above statement, the third chapter tries to address the question of what is the impact of a debt-free decision on the default risk of SMEs in the US market and how this substantial deviation from the optimal capital structure affects the SMEs' probabilities of failure compared to their leveraged counterparts. I forecast the bankruptcy probabilities by developing two discrete-time duration-dependant hazard models for debt and debt-free models. A comparison between the models shows that four explanatory variables: the research and development ratio, tangible assets, abnormal capital expenditure, and asset sales affect the probability of bankruptcy differently for each model, thus suggesting a potential need to treat debt and debt-free SMEs separately when modelling credit risk.

Chapter One

1. Introduction

In this chapter, I present my subject of study, the factors of failure probabilities and debt-free decisions of small and medium-sized enterprises (SMEs), and argue the need to analyse these issues from credit-risk modelling and corporate finance perspectives. By reviewing the previous studies closest to mine, I aim to provide a broad overview of the different aspects of small and medium-sized enterprises that I cover in this thesis, as well as the perspective that I adopt throughout the present investigation. First of all, I set out the main arguments that motivate my research. Specifically, I set the main research context where I document the prevalence of SMEs in the US market and their important role in the economy.

After arguing why SMEs are a particularly interesting subject of study, I detail the specific research questions that I attempt to answer in order to formulate the main thesis of the study. Specifically, the first section of the research questions documents the significance of modelling credit risk for SMEs and the increasing importance of further classifying SMEs into different size categories, namely micro, small and medium, in order to capture any differences that might exist while modelling the credit risk for each segment which might affect the lender's credit risk assessment depending on the size category. Then, in the second and third sections, I point out why an increasing number of SMEs decide to become debt-free and to what extent SMEs size segments affect the debt-free decisions. Furthermore, I try to address the question of what is the impact of debt-free decisions on the default probability of SMEs. Finally, I conclude the introduction by detailing the specific objectives that I aim to achieve in the following chapters and formulating the questions to be defended in the present thesis.

1.1. Research Context

The recent literature on small and medium-sized enterprises emphasizes the significant contribution of SMEs to an economy. The contribution to an economy by SMEs is not limited to developing countries, where scarcity of financial resources curbs the size of enterprises, but also in developed economies, including leading economies of the world such as the U.S., Japan, and Europe. SMEs, however, play an even more important role in developing economies. Studies on SMEs in developing countries show that SMEs have greater economic benefits than large firms in terms of employment generation and growth. SMEs are flexible in adapting to local needs, technology and available resources. They are more efficient than large enterprises in terms of capital investment per job created. SMEs usually use unskilled workers whose supply is in excess in developing countries. By creating employment opportunities for unskilled labour, they could increase income and reduce poverty in those countries. Therefore, development of SMEs is believed to be a way to transform the structure of the economy to support growth and reduce poverty in developing countries. Thus, promoting the development of SMEs is often a popular development strategy in developing countries.

SMEs constantly play a vital role in the US economy, where statistics from the "US Small Business Administration[1]" show that small businesses made up 99.7% of US employer firms in 2011, and they accounted for 63% of the new jobs created between 1993 and 2013. These numbers emphasize the importance of SMEs as job creation engines. Furthermore, the Bureau of Labour Statistics[2] and a study by the Economist Intelligence Unit in 2009 show that during the financial crisis SMEs continued to hire employees and create new job opportunities (EIU, 2009; Ackert and Tian, 2001).In spite of the important role that SMEs play, their potential has often been disregarded by

[1] The Small Business Administration (SBA) was created in 1953 as an independent agency of the federal

[2] Source: Bureau of Labour Statistics, BLS. For the latest employment statistics, see Advocacy's quarterly reports, www.sba.gov/advocacy/10871.

major market players such as regulators, lending institutions, and stakeholders. Hence, the existing and recently expanding literature on SMEs is still far from totally understanding their structure, the challenges to growth that they face, and the complex business dynamics in which they operate.

1.2. Research Questions

In this thesis I attempt to shed some light on certain aspects related to the SMEs' bankruptcies and capital structure. More specifically, I attempt to answer each of the research questions that head the following sub-sections. First of all, I focus on the diversity that exists within the broad SMEs category and whether this diversity affects SMEs' probabilities of failure. Then, I attempt to provide some explanations behind SMEs' choice of being debt-free in their capital structure decisions. Finally, I further investigate the effects of SMEs' debt-free decisions on their failure probabilities.

- **Do different size categories within SMEs play a role in affecting their probabilities of bankruptcy?**

Previous empirical studies on credit risk modelling focused extensively on large and listed firms. The literature documents two main approaches in this regard: the Altman (1968) approach, which uses historical accounting data to predict bankruptcy; and the Merton (1974) approach, which relies on securities market information.

Recent empirical literature has started to focus on SMEs credit risk modelling, which is mainly driven by the emerging needs of financial institutions to model for SMEs' credit risk since they require specific risk management tools and methodologies to be developed for them (Altman et al., 2010). In line with this, Dietsch and Petey (2002) argue that German and French SMEs are riskier than large firms but have lower asset correlation with each other. Altman and Sabato (2007) provide a distress prediction model specifically designed for the US SMEs sector based on a set of financial ratios derived from accounting information.

More recently, another strand of SMEs literature has emerged focusing on the importance of the diversity that exists within the SMEs segments, namely micro, small, and medium enterprises. These categories are classified in terms of the firms' management style (Wagar, 1998), access to finance (Beck et al., 2006), number of employees (El kalak and Hudson, 2015a) etc.

A limited number of studies investigate a broad dimension of research and report differences within the SMEs sectors. For example Kotey and Slade (2005) report a study on the personnel management dimension within SMEs, showing that differences exist between micro, small and medium Australian firms. Another study by De Mel et al. (2009) focuses on the innovation dimension within the different categories of SMEs. A study conducted by Beck et al. (2005) investigates the effect of firm size on the extent to which the corruption of bank officials and financial and legal issues constrain a firm's growth. They found that the smaller the firm the more it is affected by these constraints.

Another dimension studied is the leverage decisions and capital structure, investigated by Ramalho and da Silva (2009) who report a study on Portuguese SMEs showing that different size structure (micro, small, medium, and large) affect significantly the determinants of leverage decisions.

Not only researchers recognise the importance of size categories within SMEs but banks and other financial institutions also have finally started to consider these segments while developing customised credit risk modelling, in order to be protected against any potential risks associated with in each category. Therefore, more attention has been given to the effect of SMEs categories on default probabilities and to what extent firm size matters in prediction of default. The empirical literature indicates that the larger the firm is the more stable its cash flow and the more diversified it is likely to be (Gill et al., 2009). This leads to a negative relationship between firm size and default probabilities

(Pettit and Singer, 1985). A recent study by (Altman et al., 2010; Gupta et al., 2014) investigates the financial and non-financial factors that influence failures within each of the UK SME categories (micro, small, and medium). Their findings provide strong evidence that the credit risk characteristics of firms within the broad SMEs segment vary, suggesting a separate treatment for each of the categories to achieve better pricing of credit risk. In light of the studies just reviewed, I attempt to continue and improve on the latter study in several ways. First, I test the SME categories on a geographically different sample (US firms) and in doing so I emphasize the substantial soundness and significance of distinguishing between the broad SME categories. Second, from a methodological point of view, while applying discreet hazard models, the estimation of baseline hazard should be done using time dummies (Beck et al., 1998) or some other functional form related to time (Jenkins, 2005). However, Gupta et al. (2014) have created the baseline hazard while including an insolvency risk variable, which distorts the idea of baseline hazard. Moreover, they have utilized the ROC curve as their out of sample validation technique. This technique has been criticized by many scholars who argue that it generates misleading results. In this study, I have applied certain improvements to their paper by establishing a more precise baseline hazard function based on time dummies and applied an out of sample evaluation technique similar to the one used by Shumway (2001) which provides more accurate results.

- **What are the reasons behind SMEs' choice of debt-free capital structure decisions? And to what extent do different SMEs size segments affect the debt-free decision?**

Since the seminal work of Modigliani and Miller in 1958, two predominant theories of capital structure, namely, the "Optimal Trade-off" and "Pecking order" hypotheses, try to explore the reasons behind the choice of debt and equity financing and to determine the optimal level of debt-equity that should be held in the firm. The development of these two theories resulted in several hybrid hypotheses. For example, Fischer et al. (1989) suggest the dynamic capital structure hypothesis which is derived from the trade-off theory. They suggest that firms deviate from their optimal capital structure due to economies of scale. However, firms return to their targets using debt financing.

Both theories advocate the use of debt because of either tax benefits or lower costs of asymmetric information. However, neither the trade-off theory nor the pecking order theory is able to explain why so many firms across countries follow a debt-free policy. This extreme debt puzzle refers to the idea that certain firms prefer to have no leverage compared to that which would maximize the firm value from a static trade-off theory point of view (Miller, 1977; Graham, 2000). A study by Korteweg (2010) encourages zero-debt firms to reach their optimal leverage ratio so they can achieve higher firm value by 5.5%. Recently, studies on dynamic trade-off theory find relatively lower optimal leverage ratios (Goldstein et al., 2001; Strebulaev, 2007); however they are still unable to provide explanations for the zero-debt usage in some firms.

With an increased number of firms tending to be zero-leveraged[3], a growing body of literature tries to solve this debt-free puzzle and find the main determinants behind this choice of extreme capital structure (see for example Strebulaev and Yang (2013); Bessler et al. (2013); Byoun and Xu (2013)). However, to my knowledge, there is no study attempting to investigate the determinants of debt-free decisions within SMEs. Studying the zero-debt puzzle in SMEs would help to better understand their capital structure decisions. Moreover, the zero-debt phenomenon is considered to be a special case of the low-leverage puzzle, which refers to the fact that some firms tend to keep low leverage ratios in their capital structure relative to the normally expected models of capital structure. Therefore, I investigate the reasons behind SMEs' choice of being

[3] Bassler et al. (2013) report that one out of every four listed firms in the developed markets retain from using debt.

debt-free in their capital structure decisions. Furthermore, I study to what extent different SMEs size segments (namely micro, small, and medium) affect the debt-free decision. In order to answer this question I test empirically the theoretical implications that might affect the capital structure decisions within SMEs such as the borrowing constraints, SMEs valuation and financing activities, investment opportunities, profitability, and dividend payments.

- **What is the impact of the debt-free decision on the default risk of SMEs and how does this substantial deviation from the optimal capital structure affect the SMEs' probabilities of failure compared to their leveraged counterparts?**

My third chapter explores the zero-debt puzzle of SMEs providing potential explanations for the reasons behind the choice of zero-debt along various dimensions. I examine a number of economic mechanisms that are believed to explain the phenomenon of extreme debt conservatism in SMEs. I find that borrowing constraints and financing activities play a significant role in the debt-free capital structure decisions of SMEs.

As a follow up question to my previous chapter, I investigate whether debt-free decisions in the SMEs play any significant role in affecting their probabilities of failure. To my knowledge there is no research reported in the SMEs literature that explores the main determinants of the failure probabilities of debt-free SMEs. This is an important question especially as debt-free SMEs deviate substantially from their optimal level of capital structure according to the main theories of capital structure; hence they might face lower risk-adjusted return leading to an increased probability of bankruptcy (Bessler et al., 2013). On the other hand, using no debt in their capital structure might make these SMEs less exposed to leverage risk, which is usually associated with higher failure probabilities (Altman and Sabato (2007); Altman et al. (2010)). Hence, it is important to distinguish what factors affect the probabilities of bankruptcy for debt and debt-free SMEs. In this chapter I contribute to the growing literature on SMEs by addressing the question of what is the impact of the debt-free decision on the default risk of SMEs in the US market and how this substantial deviation from the optimal capital structure affects the SMEs' probabilities of failure compared to their leveraged counterparts.

1.3. Research Objectives

Previous theoretical developments in the SMEs literature and the empirical evidence provided above lay the foundations for fulfilling the following objectives. The first objective of this study is to investigate the extent to which size affects SMEs' probabilities of bankruptcy by developing four discrete-time duration-dependant hazard models, namely for the SMEs, Micro, Small and Medium size segments.

The second objective is to examine the reasons behind SMEs' choice of being debt-free in their capital structure decisions and what are the main determinants for their choice. Studying the zero-debt puzzle in SMEs will help in better understanding their capital structure decisions. Moreover, the zero-debt phenomenon is considered to be a special case of the low-leverage puzzle, which refers to the fact that some firms tend to keep low leverage ratios in their capital structure relative to the normally expected models of capital structure.

According to the capital structure hypotheses, if firms deviate too far from their optimum they will face higher probabilities of failure. However, an increasing number of firms across countries follow a debt-free policy, preferring to have no leverage compared to that which would maximize the firm value. In line with the above statement, the third objective of this thesis is to test the impact of debt-free decision on the default risk of SMEs in the US market and how this substantial deviation from the optimal capital structure affects the SMEs' probabilities of failure compared to their leveraged counterparts.

1.4. Thesis Structure

This thesis is divided into six main chapters. The first chapter is the introduction, which presents the research context, questions, and objectives. The second chapter contains the literature review which discusses the most recent theoretical and empirical studies relating to the credit risk modelling and capital structure theories. Chapters from three to five are the empirical chapters of this thesis. Chapter three tackles the question of how different SMEs' size affects their probabilities of failure. The fourth chapter tries to solve the SMEs' extreme debt conservatism puzzle. The fifth chapter extends the fourth chapter by further tackling the question of how SMEs being debt-free affects their probabilities of failure. Chapter six concludes the whole thesis, provides the research findings and contribution and shed some light into future research.

Chapter Two

2. Literature Review

Risk is a term often used to indicate the uncertainty associated with a potential loss. Risk is the umbrella term for multiple types of uncertainties that a firm encounters from different sources. Olsson (2002) discusses the existence of several types of risk that may impact the firm's performance in a significant way. Among these types is the market risk which is known as the risk of losses that arises from factors beyond the control of the firm such as the risk associated with foreign exchange rates, market prices' volatility, commodity prices, natural disasters, terrorist attacks etc. This risk, also called the systematic risk, cannot be eliminated through diversification, although it can be hedged against. Another type of risk is the regulatory risk which results from failing to comply with adverse changes in regulations made by the government or a regulatory body. These regulatory changes may lead to increased operational cost, reduction of the investment attractiveness, or changes in the competitiveness landscape. Business risk is classified as one of the major types of risk that a firm faces relating to its business operations. This risk occurs due to numerous factors, including inappropriate strategies, misunderstanding of the overall economic climate etc. This risk may result in lower than anticipated profits. Therefore, it is suggested that firms with higher business risk select lower debt ratio in their capital structure in order to be able to honour their financial obligations at all times. Credit risk refers to the uncertainty related to the full or partial fulfilment of financial obligations. Related to credit risk, changes in risk grades may in turn negatively influence the market value of debt instrument. In addition, the firm may face a counterparty risk that arises due to the uncertainty of honouring the contractual obligations by the other party of the contract. Liquidity risk may be related to the counterparty risk, where an increased counterparty risk leads the firm to default on honouring its short term financial obligations. Operational risk is a form of risk that is defined by the Basel II committee as the risk of loss resulting from inadequate or failed internal processes, people and systems or external events. Operational risk can be subsumed as inefficiencies related to technology, fraud, staff, security etc. Changes in technology, market concentration, economic cycle, trade barriers etc. are considered to be possible factors of industry risk that may face the firm. This risk is limited to firms within a certain industrial segment and usually affects all stakeholders in the firm such as investors, creditors and regulators. In addition to the above types of risk, a firm may be exposed to additional risks such as political risk, environmental risk, transfer risk etc.

2.1. Introduction to Credit Risk Modelling

Credit risk is a critical area for banks and corporations and is of concern to a variety of stakeholders such as managers, institutions, customers, and regulators. An extensive number of research studies have been conducted to investigate the credit risk.

Credit risk is considered to be one of the most commonly encountered types of financial risk when doing business. It is defined as the risk of loss of a financial reward due to the debtor's failure to repay a loan or other line of credit. In other words, credit risk arises when an individual or a corporation lends money or provides goods or services on credit to another entity. This uncertainty of debt repayment is usually compensated by a premium or interest payments from the debtor to the lender.

There are many types of credit risk. At the heart of credit risk is the default risk, which arises when a debtor fails to meet their legal obligations according to the debt contract. Default risk takes different forms such as corporate bankruptcy, bond default, mortgage foreclosure, and credit card charge-off. Moreover, other different types of credit risk exist, for example uncertainty about the severity of loss upon the default event, repayment delinquency in retail loans, and the unexpected change of credit rating.

With the rapid development of financial markets around the world, banks are no longer the only fund providers in the market. Nowadays, new institutions such as hedge funds, mutual funds, and funds of funds are gradually emerging as important players benefiting from the creation of modern financial instruments like asset based lending, bonds, commercial papers etc. and the associated economic gains.

Banks and other lending bodies are exposed to various risks, especially credit risk resulting from lending capital to segments like small businesses, micro finance, the mortgage market etc. The exposure to diverse lending activities and the added business complexities of the activities of these lending institutions make them face increased default probabilities. This, in turn, has forced them to review their credit risk analysis and work towards the innovation of advanced credit risk management by developing better credit information systems.

Another challenge facing the institutional lenders is the rapid changes in regulations such as the implementation of Basel I, Basel II, and more recently Basel III. These regulatory changes are usually related to major financial crises such as the real estate crisis of 1989, the Asian crisis of 1997, the 2007 financial crisis, and the Euro zone debt crisis. These challenges imposed an increased necessity for the development of sound credit risk management policies and tools. Institutional lenders have already started developing innovative financial products to countervail and manage such these crises, for example, collateralized mortgage obligations, asset backed securities, or more recently the credit derivatives which have been designed to create some kind of insurance mechanism for these lending institutions. However, some of these innovative products were misused by some institutional investors and back fired to partially cause the recent financial crisis of 2007.

2.2. The Two Worlds of Credit Risk

Credit risk has been the subject of considerable research by both academics in finance and practitioners in industry. There are two parallel worlds of credit risk based on the type of default probability, one being implied and the other being actual. The implied credit risk corresponds to the risk-neutral default probability implied from the credit market data, which is known as "Spread Risk" e.g. corporate bond yield. The actual credit risk refers to the direct observations of default, this is also known as the "Default Risk".

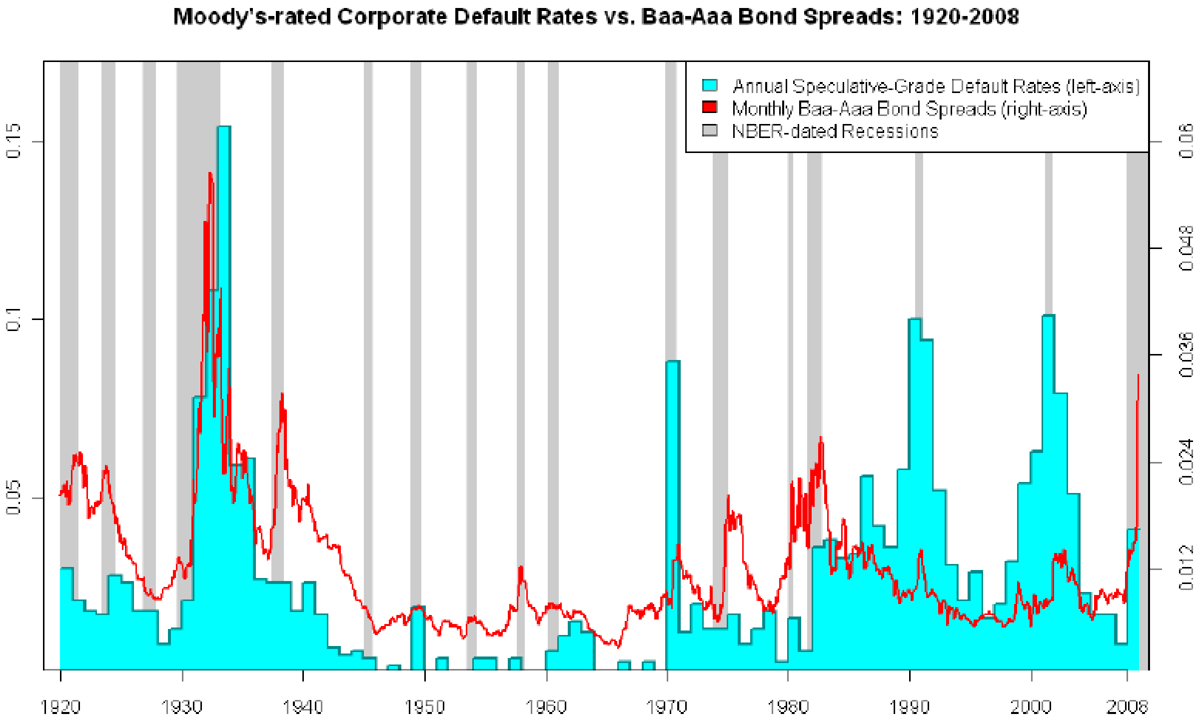
2.2.1. Spread Risk

Change in the expectations about the likelihood of loss from default is caused due to changes in the credit quality of the debtor or counterparty, for example, price or yield change of a bond as a result of credit rating downgrades.

Theoretically, the credit spread is expected to co-move with the default rate. Figure 2.1 provided for illustration, plots the Moody's rated corporate default rate and Baa-Aaa bond spread ranging from 1920 to 2008. The shaded background represents the NBER's latest announcement of recession dates. The movement of the two time series is clearly different from each other. This lack of matching is called the credit risk puzzle. Therefore, it can be argued that the actual default rates could be successfully implied from the market data of credit spreads by none of the existing structural credit risk models. The recent empirical corporate finance literature adopts two approaches to examine the validity of structural credit risk models. Researchers have either compared actual credit spreads with those implied by a fully calibrated structural model (notably, Huang and Huang (2012)), or else they have regressed changes in spreads upon a reduced form of the structural model (Longstaff and Schwartz, 1995; Collin-Dufresne et al., 2001).

Longstaff et al. (2005) suggest that illiquidity may be a possible explanation for the failure of these models to more properly capture the yield spread variation. A security cannot be traded quickly enough in the market to prevent loss.

Figure 2.1 Moody's-rated corporate default rates vs. Baa-Aaa bond spreads



2.2.2. Default Risk

It is the study of default probability bottom up from the actual credit performance. The 1997 Asian economic crisis and the Russian crisis that followed increased the attention to studies of quantitative prediction models for bankruptcy. More recently, the financial crisis of 2008 highlighted the weaknesses of existing risk management practices within the lending environments and risk assessment, especially at the micro level. The risk of failure at the firm level is of major importance since it affects the firm's entire existence and it has a high cost to the firm, collaborators (firms and organisations), society and the country's economy (Warner, 1977). Therefore, different players such as shareholders, creditors, employees, along with regulators require timely information on the failure risk probability of the firm. Consequently, the development and use of models able to predict failure can be very important in two different ways. First, as early warning systems, such models are useful to those (e.g. managers and authorities) that can take action to prevent failure. These actions include decisions about merger of distressed firms, liquidation or reorganisation and associated costs (Casey et al., 1986). Second, such models can also be useful in aiding decision makers of financial institutions in evaluating and selecting firms to collaborate with or to invest in. Such decisions have to take into account the opportunity cost and the risk of failure. Since business failure prediction became a field of study, researchers have introduced a plethora of methods for the classification and selection of methods. Different views, requirements and reliability needs have led researchers to use more sophisticated methods. Recently, for lenders such as banks, developing effective “Internal Rating Systems” for corporate risk management requires the design of adequate default probability models that incorporate the specific characteristics of each corporate sub-population such as SMEs, private firms, listed firms, and sector specific firms. In addition, they should take into account the macro environmental changes specific to each country or period of time, while being attuned to the availability and timelines of data (Hernandez and Wilson, 2013).

2.3. Main Default Models

In spite of these different methods of bankruptcy prediction and their added complexity to account for different aspects of the firm’s bankruptcy, three main dominant approaches can be classified in the literature for modelling default probability, namely, (i) traditional models which are based mainly on accounting information while using linear discriminant analysis (e.g. Altman (1968)), (ii) contingent claims-based (CCB) models that view equity as a call option on assets (Merton,1974; Bharath and Shumway, 2008), and (iii) survival analysis models (also known as hazard models) which have the ability to assess failure risk using both accounting and market information while incorporating the time to failure in the prediction probability (Shumway, 2001). From another perspective, it is debated in the literature whether models should be given superiority based on their theoretical underpinnings (Vassalou and Xing, 2004) or their empirical performance (Bauer and Agarwal, 2014). Bauer and Agarwal (2014) proposed three dimensions on which the discriminatory power of the models can be assessed: (i) to what extent the model can distinguish between failure and non-failure, (ii) the incremental information about bankruptcy captured by different models, (iii) and the performance of the models when the costs of misclassifying a company that failed are different from the costs of misclassifying a non failed one. Depending on the context, the relative significance of these dimensions varies. For example, if the main purpose is to assess whether different models carry information incremental to each other then the tests of information content are more relevant, while if the objective is to identify the most accurate model then the model with the highest accuracy ratio should be selected. Below I present the three main approaches in more details.

2.3.1. Traditional Models

Traditional bankruptcy prediction models have used either accounting models or bond market information to estimate a firm’s default risk. The accounting data-based bankruptcy prediction models mainly utilize publicly available accounting information extracted from firms’ financial statements to assess the bankruptcy risk. These models are designed to identify linear combinations of ratios which are able to distinguish between groups of failed and non-failed firms through the use of discriminant or logit models.

One of the most widely used accounting models in the bankruptcy prediction literature is that of Altman (1968) which is also known as the z-score. The first stage in building this model was to compute over 80 carefully selected ratios from the accounts of samples of 46 failed and 46 solvent industrial firms. Then using, inter alia, stepwise linear discriminant analysis, the z-score model was derived by determining the best set of ratios which, when taken together and appropriately weighted, distinguished optimally between the two samples. This model was later readjusted for the UK market by Taffler (1983), and then it was recently modified by Agarwal and Taffler (2007). Dichev (1998) examines the relation between bankruptcy risk and systematic risk. Using Altman's (1968) z-score model and Ohlson (1980) conditional logit model, Dichev computes measures of financial distress and finds that bankruptcy risk is not rewarded by higher returns.

Despite the extensive use of accounting models in the literature, several concerns usually arise while implementing such models in estimating the default probability. Methodologically, Zmijewski (1984) shows that these models are biased as they typically oversample failed firms during model development. Mensah (1984) argues that as ratios change over time, regular re-estimation of the models is important to retain their utility. However, Begley et al. (1996) and Hillegeist et al. (2004) state that only updating the model coefficients does not enhance the performance, therefore such models have to be redeveloped frequently.

Moreover, accounting models are often criticised for not relying on theoretical underpinnings. Furthermore, they use information derived from financial statements. Such information is inherently backward looking, since financial statements aim to report a firm's past performance, rather than its future prospects (Vassalou and Xing, 2004). Hillegeist et al. (2004) argue that accounting data is by nature prepared on a going concern assumption; hence their use in predicting the future, especially one that involves violating the going concern assumption itself, is fundamentally flawed. In line with these arguments, Agarwal and Taffler (2008) state that (i) differences in the reporting standards of financial statements (e.g. conservatism and historical cost accounting) may hinder the representation of the economic value of assets, (ii) the reliability of accounting information may be subject to question, e.g. the possibility of management manipulation of the accounting data.

As mentioned, an alternative source of information for calculating default risk is the bonds market. One may use bond ratings or individual spreads between a firm's debt issues and an aggregate yield measure to deduce the firm's risk of default. When a study uses bond downgrades and upgrades as a measure of default risk, it usually relies implicitly on the following assumptions: that all assets within a rating category share the same default risk and that this default risk is equal to the historical average default risk. Furthermore, it assumes that it is impossible for a firm to experience a change in its default probability, without also experiencing a rating change.

Typically, however, a firm experiences a substantial change in its default risk prior to its rating change. This change in its probability of default is observed only with a lag, and measured crudely through the rating change. Bond ratings may also represent a relatively noisy estimate of a firm's likelihood to default because equity and bond markets may not be perfectly integrated, and because the corporate bond market is much less liquid than the equity market.

2.3.2. Contingent Claims-Based Models

A standard structural model of default timing assumes that a corporation defaults when its assets drop to a sufficiently low level relative to its liabilities. For example, the models of Black and Scholes (1973), Merton (1974), Fischer et al. (1989), and Leland (1994) take the asset process to be a geometric Brownian motion. In these models, a firm's conditional default probability is completely determined by its distance to default, which is the number of standard deviations of annual asset growth by which the asset level (or expected asset level at a given time horizon) exceeds the firm's liabilities. In other words, these models view equity as a call option on the firm's assets, and the probability of going bankrupt is simply the probability that the call option is worthless at maturity. These contingent claims-based models have dominated the second generation of bankruptcy prediction models; taking advantage of their ability to overcome the shortcomings of traditional bankruptcy prediction models. For example, these models rely on strong theoretical underpinnings as they draw on the Black and Scholes (1973) and Merton (1974) option pricing framework, unlike the traditional based models which are criticised for their lack of theoretical groundings. Furthermore, in efficient markets, prices reflect both historical financial information (i.e. accounting data) as well as the individual and market-wide outlook of a business, which accounting based models do not take into account.

The Black and Scholes (1973) and Merton (1974) default prediction models (also known as the Black-Scholes-Merton, BSM) have been among the most influential and widely used models in corporate finance in the past four decades. The BSM model has been widely used to investigate, inter alia , default probabilities and recovery rates (e.g. Bruche and González-Aguado (2010)), default risk and returns (Chava and Purnanandam, 2010; Da and Gao, 2010; Li and Miu, 2010; Garlappi et al., 2008; Vassalou and Xing, 2004), default risk and executive compensation (Kadan and Swinkels, 2008) and the effect of one firm's default on the likelihood of other firms defaulting which is also known as default correlation (Lando and Nielsen, 2010; Campbell et al., 2008).

Various attempts have been made over the years to modify and extend the BSM model. Some papers, including Stein (2007), Engelmann et al. (2003), and Bharath and Shumway (2008) argue that BSM model can easily be improved upon. Other papers, including Kealhofer (2003), argue that the BSM-like model originally developed by the KMV Corporation captures all of the information in traditional agency ratings and well-known accounting variables. Duffie et al. (2007) show that the default probabilities of BSM's model have significant predictive power over time, which can generate a term structure of default probabilities. Campbell et al. (2008) estimate hazard models that incorporate both BSM variables and other variables for bankruptcy, finding that BSM seems to have relatively little forecasting power.

A recent notable extension by Bharath and Shumway (2008) shows that using market-based estimates of firm value, rather than solving the simultaneous equations of the theoretical BSM model, results in improved predictions. Charitou et al. (2013) suggest that there are merits to using simpler, more direct specifications. Using a straightforward estimate of the face value of debt as the bankruptcy default trigger and an estimate of the weighted-average debt maturity (rather than assuming debt maturity equal to one) generally improves the forecasting ability of the BSM model (especially when used in conjunction with the direct volatility measure).

Like any other approaches, contingent claims-based models suffer from certain shortcomings. First, Duffie and Lando (2001) show that if the distance to default cannot be accurately measured, then a filtering problem arises, and the default intensity depends on the measured distance to default and also on other covariates that may reveal additional information about the firm's conditional default probability. More generally, a firm's financial health may have multiple influences over time. For example, firm-specific, sector wide and macroeconomic state variables may all influence the evolution of corporate earnings and leverage. Second, Saunders and Allen (2010) argue that such models are unable to differentiate between the different durations of debt since they assume a zero-coupon bond for all liabilities. Avramov et al. (2013) argue that distressed firms are prone to suffer from market micro structure problems such as thin trading or limitation to short-selling which might result in prices deviating from fair values for an extended period.

2.3.3. Survival Analysis Models

The latest generation of bankruptcy prediction modelling is dominated by survival analysis. This analysis is concerned with determining the relationship between the characteristics of a firm and predicting the probability and timing of a particular event (default). Survival analysis is often known as the hazard rate modelling technique. The hazard rate is defined as the conditional probability that an event of interest occurs within a particular time interval. By definition, an event is the movement from one state to another that can be spotted at a point in time. The time to an event is the main variable of interest in survival analysis, which in bankruptcy studies is the incorporation of a firm to bankruptcy filing. Two types of hazard models are used according to the time scale used to measure the survival time, which is the time or duration of the event. If the event time is known accurately then continuous-time hazard models are employed such as the Cox model, whereas if the event time takes place within a given time interval and the exact time of occurrence is unknown then discrete-time hazard models are applied (Rabe-Hesketh and Skrondal, 2008). Usually, in bankruptcy studies the time scale is measured in quarterly or annual units since the firm may file for bankruptcy anytime within a quarter or year. Hence the choice of discrete-time hazard models is more appropriate from a theoretical point of view. However, there is no clear justification for the use of either method in the literature; some scholars apply discrete-time models (Campbell et al., 2008; Bauer and Agarwal, 2014) and others, continuous-time models (e.g. Chen and Hill (2013). Another trait of hazard models is their ability to incorporate time-varying covariates. Among the studies that use time-varying covariates are McDonald and Van de Gucht (1999), Chen and Hill (2013) and El kalak and Hudson (2015a), whereas the study by Shumway (2001) was conducted using time-dependant covariates.

One advantage of using hazard models is the incorporation of accounting and market data rather than just relying on accounting data as in the traditional models. Chava and Jarrow (2004) use both types of data in their hazard model which uses ratios such as profitability, liquidity, market volatility, and market price. In addition, Campbell et al.

(2008) further enhance the bankruptcy hazard models by using ratios that combine accounting variables in the numerator (e.g. profit) and the market value of total assets in the denominator.

2.4. Comparison between the Main Default Models

In this subsection, I provide a comparison between the three types of default models employed in academic studies. I discuss the main studies that partially or fully compare the performance of these models. This comparison focuses on the main characteristics of the default-risk models which are: (i) the form of the model, whether it is a structural or reduced form[4]. (ii) Static vs. non static models. (iii) the extent to which default risk models include market based data rather than just relying on accounting data (e.g. Bauer and Agarwal (2014)).

The main differences between the different default models can be summarized by the following points. Firstly, reduced form models suppose that default time is governed by an intensity process dependant on the current state variables, with the variables being empirically selected (Chen and Hill, 2013). Survival analysis models, also known as intensity models, are reduced form models. On the other hand, structural form models are based on theoretical underpinnings derived from the theories of Black and Scholes (1973) and Merton (1974). Secondly, according to Shumway (2001) static models are assumed to be single-period models, whereas non-static models are known as multi-period models or duration models. This classification is further explained by Duffie and Singleton (2012) who categorise default risk models by their methodological approach as duration, qualitative response, and discriminant models, whereas they classify qualitative response and discriminant models as single-period models. Static models are defined as single-period models where the data for the firms are observed only once, even though the firms' data spins several years. These are also known as time invariant

[4] For more details see Bharath and Shumway (2008).

models. The traditional models are considered to be examples of static models. On the other hand, non-static or multi-period models observe each firm at risk of bankruptcy in each period. Both survival analysis and contingent claims based models are examples of non-static models. Shumway (2001) criticizes static models for being biased and inconsistent in the estimation of the model parameters due to the misspecification of the maximum likelihood function, which fails to consider the firms at risk of bankruptcy in each period. Moreover, non-static models are superior to static models based on their efficiency since they use all the data available for each firm at each point in time, unlike static models, which utilize only one year of data.

Thirdly, both survival analysis and contingent claims based models incorporate market data into their models. Furthermore, it is argued by Chen and Hill (2013) that BSM are assumed to be more heavily reliant on market data than the survival analysis models. This argument is in line with the study of Bharath and Shumway (2008), which used a hybrid model that incorporates BSM model output as one input into the Cox model (Survival Analysis type). On the other hand, traditional models suffer from the reliance on accounting information only which in turn suffers from problems related to accounting policy standards, historical data, and managerial discretion.

There are a considerable number of studies in the existing literature that compare the performance of the default risk models. The first strand of literature tests the performance of traditional against contingent claims approaches. Hillegeist et al. (2004) compare the contingent claims based measure with the Ohlson (1980) o-score and Altman (1968) z-score using information content tests. They find that their contingent claim based model has relatively more explanatory power about predicted bankruptcy than either of the two scores. However, they find that both traditional scores carry significant, incremental information, and the contingent claims based model does not reflect all available market-based information; hence it is not a sufficient statistic for predicting the probability of bankruptcy. Reisz and Perlich (2007) estimate the probabilities of bankruptcy in a model where common equity is viewed as a down-and-out barrier call option and compare it with the standard Merton (1974) option framework as well as the accounting based Altman (1968) z-score model. They find that their model displays better calibration and discriminatory power than that of Merton (1974). However, in contrast to Hillegeist et al. (2004), they report that the accounting based models outperform structural models for a 1 year prediction horizon, but lose relevance as the forecast horizon is extended.

Agarwal and Taffler (2008) compare the performance of the UK-based z-score model of Taffler (1984) against the Merton (1974) model using receiver operating characteristic (ROC) curves and information content tests. Furthermore, they use the framework of Stein (2005) and Blöchlinger and Leippold (2006), and extend the analysis to compare the market shares, revenues and profitability of banks employing these competing models, taking into consideration differential error misclassification costs. They report that the difference between the two models is statistically not significant, although the z-score model is marginally more accurate. Moreover, in a competitive loan market, they show that z-score approach leads to significantly greater bank profitability. Finally, relative information content tests find that both the z-score and contingent claims based approaches yield estimates that carry significant information about failure, but each model captures different aspects of bankruptcy risk.

The evidence in the literature that compares the performance of survival analysis and traditional models shows that the duration models are far superior to traditional models. For example, the study by Shumway (2001) shows that most of the accounting models used in the previous literature such as Altman (1968) and Zmijewski (1984) add little predictive power in forecasting bankruptcy compared to the hazard models. Shumway emphasizes the importance of adding market variables to the accounting ones to enhance the accuracy of forecasting bankruptcy. This study has been further extended by Chava and Jarrow (2004) who further support the incorporation of market variables to increase the forecasting accuracy. Charalambakis et al. (2009) also report a similar conclusion when comparing both models in the UK market.

The third strand of literature tests the performance of hazard models and contingent claims based models. Campbell et al. (2008) argue the superiority of hazard models to the contingent claim based model of Moody's KMV in information content tests. In addition, they also argue that their hazard based model outperforms the Shumway (2001) model based on higher pseudo-R2. A study by Christidis and Gregory (2010) designed an improved hazard model to that of Campbell et al. (2008) by adding accounting and macro-economic variables. They test their model on the UK market and claim that their model outperforms that of Campbell et al. (2008); however they could not provide evidence of the outperformance of their model over the traditional models.

It can be shown that the existing literature compares the models using one or two of the three main approaches and fails to reach a unified conclusion about the superiority of one model over the others for predicting bankruptcy probabilities. In addition, previous studies in the literature fail to provide a unified out performance test to compare the superiority of one model over the others, where some studies use either ROC curve analysis (Chava and Jarrow, 2004), information content tests (Hillegeist et al., 2004) or out of sample ranking test (Shumway, 2001). In order to overcome these issues, a new strand of literature emerged comparing all the three approaches together. Bauer and Agarwal (2014) provide a full comparison between the three main approaches where they implement the hazard models of Shumway (2001) and Campbell et al. (2008) to represent the survival analysis models. Moreover, they use the naïve version of the contingent claims based approach of Bharath and Shumway (2008) and for the accounting models they employ the Taffler (1983) and Agarwal and Taffler (2007) models. In addition, they test the outperformance of each model in predicting the probability of bankruptcy using several tests. Their ROC analysis demonstrates that the hazard models are superior to the other models. Furthermore, the information content tests show that the hazard models subsume all bankruptcy related information in the contingent claim based model of Bharath and Shumway (2008) and the z-score model of Taffler (1983).

2.5. What is Failure?

A key issue in the studies of bankruptcy is what is meant by corporate bankruptcy. Failure can be defined in many ways, depending on the specific context of the investigation. The majority of the existing literature pertaining to bankruptcy prediction models utilizes the juridical definition of failure which is known as bankruptcy in the United States and insolvency in the United Kingdom. Examples of studies that have applied this definition are Ward and Foster (1997); Van Caillie and Dighaye (2002); Daubie and Meskens (2002); Charitou et al. (2004). The legal criteria for defining failure have certain advantages such as the legal failure event can be accurately and objectively dated for use as an outcome variable. Moreover, the definition of failure is applied in order to model the probability of bankruptcy using binary choice models where failing and non-failing firms are clearly separated from each other (Balcaen and Ooghe, 2006).

On the other hand, this legal definition has been criticized in several respects. For instance, bankruptcy involves lengthy legal processes, hence there exists a long time lag between the moment when a firm experiences serious problems that make it impossible to operate in a normal way, or the moment when it ceases to record annual accounts, and the final juridical exit in the form of a bankruptcy (Theodossiou, 1993). Companies in the UK show a time gap of 1.17 years on average between the onset of financial distress and the date of legal default (Hernandez and Wilson, 2013), while in the US, firms stop reporting accounts approximately two years before the bankruptcy (Theodossiou, 1993).

Furthermore, it is argued that some firms may file for bankruptcy without showing real signs of failure. This situation might happen when some firms decide to file for bankruptcy to get rid of their debts and restart their activities with a clean sheet. Hill et al. (2011) differentiate between unexpectedly bankrupt firms which do not show any signs of financial distress and firms in real financial distress[5].

Therefore, an increasing number of studies employ a bankruptcy definition based on 'financial distress' (Doumpos and Zopounidis, 1999; Platt and Platt, 2002; Pindado et al., 2008; Hernandez and Wilson, 2013) or on failure-related events such as cash insolvency (Laitinen, 1994), loan default (Ward and Foster, 1997), capital reconstructions, major closures, forced disposals of large parts of the firm, informal government support, and loan covenant renegotiations with bankers (Agarwal and Taffler, 2003). Wruck (1990) classifies a firm as financially distressed when its cash flow is not enough to cover its current financial obligations. Furthermore, Asquith et al. (1994) define a firm as being in financial distress if its earnings before interest, taxes, depreciation and amortisation (EBITDA) are less than its reported financial expenses for two consecutive years beginning in the year following a junk bond issue, or, if in any other year, EBITDA is less than 80% of its interest expenses.

2.6. SMEs Failure

Measuring and tracking the probability of failure of small and medium-sized enterprises is a difficult task. This is mainly due to the difficulties associated with locating and identifying these firms, in addition to determining the exact reasons for their failure (Altman et al., 2010). Despite the existence of these difficulties a considerable amount

[5] For a more detailed discussion on the shortcomings of the legal bankruptcy definition see Balcaen and Ooghe (2006).

of research has been carried out to investigate the rates and causation of such failures (see for example Headd (2003); Carter and Auken (2006); and Altman et al. (2010)).

The failure of new firms should not always be taken as implying economic inefficiency, since it might enhance social welfare and reduce industry costs. In addition, according to Knott and Posen (2005) not all business failures are due to financial difficulties. Starting from this argument, one should take into consideration before analysing and studying business failure rates that it is essential to distinguish between firm failure and firm planned exit strategies where the business is actually healthy enough to continue operation (Headd (2003); and Bates (2005). In line with this, Watson and Everett (1996) argue that some financially successful firms might decide to close for different reasons such as closing to limit losses, change of ownership, opportunity cost, switching costs, personal decisions etc.

The literature has further investigated the reasons behind business failures. Altman et al. (2010) mention two principal reasons for firms' closure, which are lack of planning and insufficient capitalisation. Hutchinson and Xavier (2006) suggest that financial difficulties are the main factor for SMEs' failure, while others such as Peacock (2000) report that poor managerial skills are behind these failures. Carter and Auken (2006) classify default factors into direct and indirect costs. They suggest that direct costs such as lack of knowledge, economic climate, and debt financing are the main reasons for firm failure, while indirect costs such as self-employment, personal collateral, and self-esteem can play a secondary role.

In their paper Altman et al. (2010) suggest that different asset size segments lead to different SMEs' insolvency risk behaviour. They find that the relationship between asset size and insolvency risk appears to be non-linear, with insolvency risk being, in different regions, an increasing and decreasing function of size. They justify their finding by the argument that the lower the asset values the less likely the firm to be pursued by creditors for bankruptcy proceedings, since little opportunity remains for creditors to recover their debts. However, when the firm's assets value is higher, insolvency proceedings become more attractive for creditors. Therefore, insolvency risk increases with increasing asset size. However, after a certain level (threshold level) this increase in bankruptcy risk starts to decline with additional increases in asset value. This finding is further supported in the literature that finds a non-monotonic impact of size (for more details see, Brüderl et al. (1992); Falkenstein et al. (2000); and Hamerle et al. (2006)).

2.7. SMEs' Definition

Given the important role that SMEs play as powerful economic engines of growth and development for the worldwide economy, regulators and policy makers have started to realize the necessity of better understanding the challenges to growth and complex business dynamics of SMEs. An important step towards the creation of a favourable business environment and enhancement of the process of policy formulation is to set up a clear and definitive definition of SMEs.

To date, countries have failed to agree a general definition for small and medium sized enterprises. Therefore, each country defines its SMEs according to a particular set of firm characteristics and quantitative variables. The most used variables in distinguishing small from large firms are the legal status, number of employees, independence, employment, industrial sector, asset size, and capital investment. The two main economic zones that provide detailed definitions for SMEs which are of interest to my study are the European Union and the US.

The 1996 law concerning the SMEs operating within the European Union Framework was updated in 2003 and provides a widely accepted definition of SMEs taking into account the new Basel rules. The law defines SMEs as firms having fewer than 250 employees with annual turnover of less than €50 million in sales. In 2005 a new definition from the EU came into force further classifying SMEs into three categories, namely, micro, small and medium enterprises. They defines a firm as ‘micro’ if it has fewer than 10 employees and an annual turnover of under €2 million; ‘small’ if it has fewer than 50 employees with an annual turnover of less than €10 million, and ‘medium’ if it has fewer than 250 employees with an annual turnover of less than €50 million.

The Small Business Administration (SBA) is the main organisation that has been created by the US Congress to deal with issues relating to SMEs in the US. The SBA is also considered to be the major authority that defines SMEs in the US. A small business is defined in terms of the average number of employees and the average annual receipts. In addition, the SBA defines a number of other criteria to qualify as a small business. Such a business (i) is organised for profit; (ii) has a place of business in the US; (ii) contributes to the US economy by paying taxes or using American products, materials, or labours; (iv) is independently owned and operated; (v) does not exceed the numerical size standard for its industry[6]. In general, two widely used size standards have been established by the SBA; the maximum number of employees should be 500 and the average annual receipts should be less than $7.5 million. However, there are a number of exceptions depending on the industry classification of the firm. However, unlike the definition provided by the EU regarding micro, small, and medium enterprises, there is no clear definition about the firms within the SMEs in the US market. Therefore, since my chapter aims to analyse the US market, I partially adopt the EU definition and try to fit it within the SBA definition for SMEs in the US, relying on the number of employees as the main criterion of classification. Therefore, I will define a firm as ‘micro’ if it has fewer than 20 employees; ‘small’ if it has fewer than 100 employees; and ‘medium’ if it has fewer than 500 employees.

[6] For detailed information about determining the business size, see http://www.sba.gov/content/determining-business-size

As the main lenders for SMEs, banks nowadays are required to take into account the different classifications of SMEs segments rather than just relying on their traditional quantitative definitions of SMEs categories. This unified definition of SMEs segments becomes highly important since, for example, a medium sized SME in a high-income country may be the same size as a large firm in a low-income country. In addition, more issues arise because most SMEs operate within the informal sector and therefore are often not considered as part of the SMEs sector, but they nevertheless represent a potential profitable market for banks serving the SME community.

Traditionally, the banking sector often avoids providing finance to the SME market given their small size, high risk and business complexity, lack of business planning and cash flow management skills, and their different operational approach compared to large firms. However, the emergence of micro finance institutions as an important player in this market has encouraged the banking sector to reconsider the SMEs financing options.

2.8. Basel Accords and SMEs

The Basel accords are a set of international banking guidelines which were introduced by the Basel Committee on Banking Supervision (BCBS). These accords propose banking regulations which are related to capital risk, market risk, and operational risk. The main purpose of these accords is to ensure that banks operate in a safe and sound manner, to enhance the risk management practices of banks, and to ensure that a minimum capital requirement is held by a bank which is sufficient to support the risks that arise in its business. In this section I will present an overview on the development of Basel accords from Basel I to Basel II, and Basel III. This will be followed by presenting the main literature that investigates the effect of the Basel accords on banks' lending to SMEs. Finally, I will discuss the main bank capital requirements for SMEs.

2.8.1. The Development of the Basel Accords

2.8.1.1.Basel I and the Credit Crunch

The 1970s and 1980s were characterised by extensive lending from banks around the world, while external indebtedness on both country and firm levels was expanding rapidly. This situation led to an increased number of international bank failures known as the credit crunch. As a consequence, the BCBS was initially established in 1975 by the heads of the G-10 countries' central banks. The BCBS drafted a set of international banking regulations to set out the minimum capital requirements of financial institutions in order to minimize credit risk. Basel I focused on credit risk and risk-weighting of assets in order to: (i) strengthen the stability of international banking system; (ii) decrease the competitive inequality among international banks through the establishment of an internationally appropriate banking system; (iii) Increase the international presence of banks. In order to attain these goals, Basel I provided the first internationally agreed bank capital ratio to facilitate the set up of minimum risk-based capital adequacy that could be applied to all banks worldwide. Basel I classifies capital as Tier I (core capital) and Tier II (supplementary capital). Then it requires the bank to create an asset classification system that groups the bank's assets into five categories according to credit risk, where the bank must maintain capital (Tier I and Tier II) equal to at least 8% of its risk-weighted assets.

2.8.1.2.Basel II and the internal Ratings-Based Approach

Basel II is the second of the Basel accords, which was developed as an extension for the Basel I accord. The second accord was first drafted as a consultative paper on 1999 and it was officially introduced in 2004. Two amendments in 2005 and 2006 have been issued to the 2004 version to take into consideration the application of Basel II to trading activities and the treatment of double default effects.

In addition to the minimum capital requirements proposed by Basel I, Basel II introduced two new concepts, namely, Supervisory Review Process and Market Discipline. These three key concepts are known as the three pillars of Basel II. These three pillars provided Basel II with more adequate tools to align regulation with best practices in risk management and offer more incentives to banks to enhance their risk management and measurement capabilities. The first pillar, which is known as "The Minimum Capital Requirements", takes into consideration three risk factors, namely credit risk, market risk, and operational risk. The credit risk measurement significantly changed compared to that of Basel I after the introduction of internal ratings based approach, in addition to the standardized approach. The preferred methods for valuing the market risk are value at risk (VaR) measure, CVaR, stress testing, and scenario analysis. Operational risk has been defined as the risk arising from execution of a company's business functions (e.g. legal risk). The second pillar of Basel II is the supervisory review. This pillar allows supervisors to measure a bank's own assessment and decide whether this assessment seems appropriate and realistic. This pillar provided an extra eye on the bank's own assessment and determined that the bank understands its risk profile and is sufficiently capitalized against its risks. The third pillar, which is the market discipline, provides yet another set of eyes by allowing market participants to better reward well-managed banks through greater transparency of banks' financial statements.

2.8.1.3.Basel III and the Qualitative Approach

Basel III was developed by a group of worldwide experts, highly reputable in the financial and banking industry. It is essentially a set of regulatory reforms that consists of standards for measuring, managing and supervising capital requirements of banks. The BCBS introduced this accord to address many of the issues associated with the recent financial crisis in the banking sector (OECD, 2014). The first Basel capital accord was presented in 1988 to tackle problems arising from the deregulation in the financial sector, followed by the introduction of Basel II in 2004 to cope with the financial innovations and risk complexity of the financial world (Ong, 2005).

Basel III aims to provide better financial stability, stronger solvency for banks, and higher liquidity rates without negatively affecting the flow of money from the credit market. This new accord is intended not only to ensure compliance with capital rules but also to enhance the quality of risk management and governance in addition to increase the transparency among banks, learning from the financial crisis.

The new Basel accord does not provide a lot of changes to its previous versions (Basel I and II); rather, they complement each other (Cardone Riportella et al., 2011). Among the key modifications introduced by Basel III are: (i) the introduction of a stringent and more simplified definition of core Tier 1 capital. This significantly improves the quality and quantity of capital while providing an extra check on the minimum common equity requirements. (ii) The implementation of a non-risk-based leverage measure designed to supplement the capitalization standards by providing a check for efficacy of capital adequacy measurements. This ratio is essential to supporting the regime by providing a simple, easy to interpret and understand sanity check of the results produced by the risk-based framework. (iii) Given that liquidity problems played a significant role in the recent financial crisis, Basel III has developed liquidity requirements, a liquidity coverage ratio and net stable funding ratio, to ensure that banks maintain a sufficient level of liquid assets at any given time. (iv) the use of capital buffers. This enables banks to increase their capital during stable periods while the countercyclical buffer helps to protect banks against the danger of rapid credit growth.

2.8.2. Basel Accords and Lending to SMEs

The treatment of SMEs played an important role in the development of the Basel accords. This is evident from the modifications that were made by the BCBS in favour of the SMEs, which emphasize that the new banking capital requirements should be flexible and not too detrimental for SMEs.

An extensive literature has studied the effect of the Basel accords on lending to SMEs. Early empirical studies attempt to find the link between Basel I and its effect on lending to SMEs, especially during the credit crunch in the US during the 1990s. The majority of articles report a statistically significant negative relationship between lending and banks' capital requirements imposed by the Basel accord (Bernanke et al., 1991; Hancock and Wilcox, 1994; Peek and Rosengren, 1995). This indicates that imposing more capital regulations on banks leads to a decrease in bank capital which in turn affects the financing of SMEs and decreases their ability to access bank credit.

There are two main improvements in the regulatory framework of the Basel II accord in comparison to the Basel I accord. The first is the ability of banks to provide their own risk assessment while determining their capital requirements through the use of different measures such as exposure to default, probability of default, loss given default etc. The second is taking into account the underlying asset risk rather than the borrower status, which makes Basel II more risk-sensitive to capital standards. The development in the regulatory framework after the introduction of Basel II by taking into account more adequate risk management practices led to an increase in the volume of studies on internal rating based approach and to the emergence of an empirical strand of literature that considers corporate bankruptcy and the probability of default using different techniques such as discriminant analysis, contingent claim-based models, and survival analysis (Shumway, 2001). Furthermore, numerous authors find that the rating/scoring system decreases the information cost, allowing SMEs to have better access to bank credit (Berger et al., 2005; Berger and Frame, 2007). Another strand of literature examines the effect of the capital requirements of banks on the financing of SMEs.

One of the main considerations that has been raised by industry members and regulators against the Basel accord II is the minimum capital requirements imposed by bank credit exposures to SMEs (Dietsch and Petey, 2002). Most of the studies find that for both European and US markets, the Basel II accord will have valuable effects on banks' capital requirements (lower) linked to the SME segment, whether if the Standardized or one of the internal rating-based approaches is used (Altman and Sabato, 2005).

Using data from the American, Italian, and Australian markets, Altman and Sabato (2005) study the impact of Basel II on banks' capital requirements. They find that the part of SMEs classified as retail can enjoy significantly lower capital requirements than the part classified as corporate. However, for SMEs treated as corporate entities, the capital requirements are considered to be slightly greater than those considered as retail entities. This leads to the assumption, in their opinion, that most banks would apply both systems simultaneously; i.e., they would consider one part of the loans granted to SMEs as corporate entities and the rest as retail entities. Moreover, they report that for all three countries, a minimum of 20% of small and medium sized enterprises must be classified as retail in order to maintain the SME capital requirement at least at the current level (8%). On the other hand, they assure SMEs that access to bank financing under the Basel II capital requirements will be easier and possibly cheaper since banks will regard SMEs lending to be more profitable. They also stress that using the most advanced risk-based pricing techniques may lead to an increase in the cost of SME financing only for lower quality firms.

Berger (2006) argues that the implementation of the advanced internal rating-based approach may not reduce the interest rates applied to credits granted to SMEs, but may be sufficient to produce a substitution effect with respect to other smaller credit institutions.

A study by Ruthenberg and Landskroner (2008) argues that large lending institutions, which are expected to widely use the internal rating-based approach, usually provide credits for secure and stable entities. On the other hand, smaller and lower-quality institutions, which are expected to use the standardized approach, tend to service riskier entities; therefore they become risky themselves. Furthermore, a considerable number of studies have been conducted on the effect of Basel II on SMEs applying datasets from different markets. For example, studies by Medema et al. (2009), Repullo and Suarez (2004), Berger and Udell (2006), and Berger (2006) for the US Market; Scellato and Ughetto (2009), for the Italian market; Schwaiger and Chen (2003), for the Austrian economy; and Saurina and Trucharte (2004) for the Spanish market.

Very few quantitative and qualitative studies have been conducted to test the impact of Basel III on SMEs' access to bank financing. Among the few qualitative studies on Basel III are the ones by Ambler (2011), Angelkort and Stuwe (2011), Schizas (2012), and OECD (2012). These papers mainly predict a higher credit cost, shorter maturity, lower volume, and delaying recovery when SMEs require funding from banks under the Basel III accord. These findings anticipate heavier burden on SMEs finance under Basel III compared to that of Basel I and II accords.

On the other hand, a study by Cardone Riportella et al. (2011) using quantitative analysis to examine the effects of Basel III on SMEs finance, reaches a different conclusion from that using qualitative analysis. The paper reports that Basel III would improve the risk assessment and enhance the loss absorbency of banks. Thanks to the recognition of collateral, regulation should not be too binding for small firms. Beside, the improved risk sensitivity could increase risk premium and so, credit cost.

2.8.3. Bank Capital Requirements for SMEs

SMEs' finance will be affected after the introduction of the new banking framework. SMEs are classified differently when applying for credit according to the approach used by the bank, whether it is the standardized or the internal rating-based approach. In addition, the treatment of SMEs as retail or corporate plays a role in determining the capital requirements. The internal rating-based approach is based on the internal estimation provided by the bank, allowing banks to compute capital requirements which are sensitive to the risk. This approach is further divided into two main sub-approaches: (i) the foundation approach where banks produce their own loss probability models (i.e. own credit ratings), but use prescribed estimates of loss given default (LGD) based on the supervisory estimates for other risk components, the loss given default (LGD), the exposure at default (EAD), and the effective maturity of the operation (M); (ii) the advanced approach where banks use their own loss probability models and loss given default models. However, while using either sub-approach, banks should always use the risk-weight functions provided in the Basel Accords for the purpose of deriving capital requirements. On the other hand, the second approach is known as the standardised approach as it is based on external credit ratings where banks apply fixed risk weighting to assets based on the credit rating given to the SME by an external credit assessment institution.

2.9. Bank Involvement with SMEs

Small and medium-sized enterprises are viewed as the backbone of any country's economy and employment. Ayyagari et al. (2007) show that SMEs account for over 50% of the manufacturing employment across 76 developed and developing countries. In addition, it is argued that most large corporations were small companies in their early stages. Hence, SMEs have high potential for growth and development, and so play a significant role in the prosperity of any economy (Beck and Demirguc-Kunt, 2006).

Despite the importance of SMEs to the country's economy, there is a perception among policymakers and researchers that SMEs lack sufficient financing and require special assistance such as governmental subsides and public guarantee funds (De la Torre et al., 2010). A number of studies support this argument and report that SMEs are more financially constrained than large corporations, and especially the lack of access to external financing is a key obstacle to their growth (Beck et al., 2005; Vos et al., 2007; Canales and Nanda, 2012).

The ‘‘conventional wisdom” on SME finance argues that financial institutions are biased against offering SME financing. Thus, many banks and other financial institutions are not interested in servicing SMEs (De la Torre et al., 2010). However, banks remain the major credit providers for SMEs. Banks usually apply a variety of lending methodologies to assess the credit risk of a particular SME, hence to decide whether and how much to lend (Berger and Udell, 2006).

There is a considerable number of lending approaches used by banks to finance SMEs. In the literature, these lending techniques are classified into four main groups: financial statement lending (based on the evaluation of information from financial statements), asset-based lending (based on the provision of collateral and its quality), credit-scoring lending (based on statistical techniques), and relationship lending (Moro and Fink, 2013). In general, two types of information can be collected while assessing the creditworthiness of SMEs: (i) hard information, which is primarily based on quantitative information (e.g., credit history, balance sheet data, amount borrowed, credit scoring); (ii) soft information, which is based on subjective and qualitative information that is difficult to be numerically represented (e.g., SME’s competence, honesty and diligent approach to management, employee morale).

2.9.1. Relationship Lending

This type of lending is based on the development of a collaborative and repeated relationship between the bank and the SME, where the bank (credit officer or bank manager responsible for credit risk assessment) collects soft information about the borrower (SME or its manager). Credit lending to SMEs is considered to be a difficult process given the informational opaqueness, moral hazard, and adverse selection problems (e.g. Stiglitz and Weiss (1981)). Therefore, long and strong relationships between borrowers and banks may lead to easy access to credit with better loan terms (Berger and Udell, 2002).

Different indicators have been proposed in the relationship lending literature to test for the main determinants of the amount of credit provided. The strength of the relationship between both parties (bank and SME) is measured by the length, the breadth, and the exclusivity of the relationship, which affect the amount of credit granted (Cotugno et al., 2013). Some empirical studies argue that a long relationship provide banks with large amounts of private information, making it possible for them to identify firms that present moral hazard and adverse selection risks (Hernández-Cánovas and Martínez-Solano, 2010), hence banks improve the credit amount and loan terms (Petersen and Rajan, 1994). A study by Berger et al. (2005) focuses on the benefits of accumulating information, especially soft information and bank exclusivity. In spite of the banks' preference for using relationship lending, this approach suffers from certain disadvantages: (i) credit officers may provide sub-optimal credit risk assessments for the borrower based on her personal judgment which might lead to more constrained loans; (ii) the amount of time and effort spent on establishing the relationship can be cost inefficient.

2.9.2. Transactional Lending

According to Moro and Fink (2013) three of the four lending categories, namely, financial statement lending, asset-based lending and credit-scoring lending are usually grouped together and regarded as one lending approach known as the transactional lending approach. This grouping is based on the main characteristic of the information used in providing the credit risk assessment where the three categories use information based on publicly available information (hard information) and because they are primarily used for loans that serve non-recurrent needs.

Recently, banks are increasingly moving away from the use of traditional relationship lending approaches towards applying different transactional lending approaches to SMEs' financing to facilitate arms-length lending. For example, credit registries provide banks with hard information on the SMEs to deduce credit performance and therefore enable the use of credit scoring to process credit lending decisions faster with reduced cost benefiting from greater economies of scale (Kallberg and Udell, 2003; Miller, 2003). Also, the use of collateral that maintains its values over time and is relatively easy to liquidate such as equipment and real estate are considered as part of the security for loans, where the higher value of collateral leads to a higher recovery rate (Grunert and Weber, 2009). Moreover, one of the advantages that transactional lending enjoys is the use of quantifiable methods that can be generalized to evaluate the credit worthiness of the SME, rather than relying on the personal judgement of the credit officer. Despite the advantages of transactional lending, there exist certain shortcomings in implementing this approach to lend to SMEs. For example, the lending cost of using quantitative techniques such as credit scoring to evaluate the credit risk of a small number of SMEs is relatively high and inefficient making transactional lending seem more appropriate for large lenders only (Allen et al., 2004). Recently, some banks have tried to overcome this problem by cross-selling services to SMEs. This strategy considers that lending is not always the main or the first product offered to SMEs and that it is often offered as a way of eventually offering a variety of fee-based services such as advisory services, savings, and payments (De la Torre et al., 2010). Another problem with using transactional lending is related to the quality, reliability, and authenticity of the hard information provided by SMEs, not to mention the level of its availability. Therefore, when providing unsecured loans, banks usually depend on relationship lending, this is based on reliable qualitative information rather than hard information.

2.10. Theories of Capital Structure

Finance scholars have found the theory of corporate capital structure a rich area for study after Modigliani and Miller's publication in (1958) where they have proposed their irrelevance theory of capital structure. This theory states that in perfect markets, it does not matter what capital structure a company uses to finance its operations. The market value of the firm is determined by its earning power and by the risk of its underlying assets and this value is irrelevant to the way the firm decides to finance its investments or distribute dividends.

Over the years, two major theories of capital structure have been developed. These two theories deviate from the perfect capital markets assumption where the "irrelevance model" works. First, the trade-off theory assumes that after accounting for market imperfections such as taxes, bankruptcy costs and agency costs, firms trade off the benefits and costs of debt and equity financing so that they find an "optimal" capital structure.

Second, the pecking order theory (Myers, 1984; Myers and Majluf, 1984) argues that following a financing hierarchy, firms minimize the problem of information asymmetry between the firm's managers (insiders) and the outsider (shareholders).

Recently, a relatively new theory of capital structure has emerged with the aim of further explaining capital structure characteristics. This theory is known as market timing theory. This theory states that capital structure evolves as the cumulative outcome of past attempts to time the equity market (Baker and Wurgler, 2002).

Two versions of the equity market timing have been proposed which lead to similar capital structure dynamics. The first is the dynamic form of Myers and Majluf (1984) with rational managers and investors and adverse selection costs that vary across firms or across time. The second version of the equity market timing approach involves irrational investors (or mangers) and time-varying mispricing (or perceptions of mispricing). Managers issue equity when they believe its cost is irrationally low and repurchase equity when they believe its cost is irrationally high (La Porta, 1996).

Some scholars do not recommend applying theories of capital structure in the SMEs sector because, as Ang (1991) argues, these theories were developed without taking into consideration small and medium enterprises. On the other hand, Michaelas et al. (1999) and Lucey and Mac an Bhaird (2006) praise these theories for allowing the formulation of testable hypotheses on the financing decisions of SMEs. Furthermore, Cassar and Holmes (2003) support the latter argument stating that corporate finance theory provides the theoretical underpinnings necessary for any research on the capital structure of SMEs with one major exception. This exception lies in theories which involve conflicts between owners and management since SMEs tend to have a less pronounced separation of ownership and management than larger firms.

This section will shed some light on the irrelevance theory of Modigliani-Miller which was the dawn to the era of capital structure research. A review on the trade-off theory and the pecking order theory; the main two theories of capital structure which emerged from the irrelevance model, will also be conducted.

2.10.1. The Modigliani-Miller Theorem

The seminal work of Modigliani and Miller (1958) played the major role to get the general consent on the theory of capital structure. According to Watson (1955), finance experts at that time doubted whether it is possible to develop any theory on capital structure. Shockingly, the irrelevance theory of capital structure was proposed in Modigliani and Miller's (1958) paper, later known as M&M. M&M's core logic is about the particular set of expected cash flows. When choosing a certain proportion of debt and equity to finance the firm's assets, the only thing the firm does is to divide up its cash flows between investors. Moreover, allowing for homemade leverage, equal access to financial markets is supposed to be for both investors and firms. The investor either creates any wanted leverage that was not offered, or gets rid of any leverage that the firm took on, yet was not wanted. Consequently, the firm's leverage has no effect on the market value of the firm.

Additionally, Luigi and Sorin (2009) classified the irrelevance theory into two essentially different types of capital structure propositions. First, the classic arbitrage-based irrelevance proposition, which is further supported by Hirshleifer (1966) and Stiglitz (1969), argues that investors' arbitrage allows the value of the firm to remain independent of its leverage. The second proposition argues that the dividend payment policy that the firm choose to follow, given a firms' investment policy, will not have any consequences on its current share price nor its shareholders' total return (Modigliani and Miller, 1963).

However, several major shortcomings still impact on the popularity of the irrelevance theory. For example, various studies have shown that the Modigliani-Miller theorem fails under a variety of circumstances. The most commonly used elements include consideration of taxes, transaction costs, bankruptcy costs, agency conflicts, adverse selection, lack of separability between financing and operations, time-varying financial market opportunities, and investor clientele effects (Luigi and Sorin, 2009). Moreover, it is difficult to test this theory with debt and firm value both plausibly endogenous and driven by other factors such as profits, collateral, and growth opportunities.

2.10.2. The Trade-off Theory

Widely used by scholars, the trade-off theory expresses a family of related theories which suggest that the trade-off between various costs and benefits is the basis of an optimal capital structure or leverage plan. The balance between the marginal costs and marginal benefits initiates the optimal capital structure.

The work of Modigliani and Miller (1953) originated the first form of the trade-off theory. After the M&M theory was criticised for relying on unrealistic assumptions, Modigliani and Miller (1963) added taxes into the M&M hypothetical theory after realising the importance of the tax merits of debt. They incorporated an interest tax shield in their model after taking into account that the amount of taxes to be paid decreased as interests were tax deductible. The inclusion of interest tax shield into the M&M theory led to an optimal capital structure where firms should use 100% debt in order to maximize their value. However, the main stream of empirical evidence refuted the extreme usage of debt so contradicted this theoretical conclusion.

While defining the trade-off theory, Myers (1984) points out several issues. First, the trade-off theory does not take into consideration the complexity of the tax code. He argues that depending on the feature of the tax code included, different conclusions can be drawn. Second, Myers asserts that bankruptcy costs must be deadweight costs not transferable costs from one claimant to another. Moreover, in his study, Warner (1977) argues that the direct costs of bankruptcy do not alone rationalise the observed borrowing among most firms as they are negligible. Furthermore, Haugen and Senbet (1978) present a thorough discussion of bankruptcy costs. Altman (1984) also confirms that as major elements associated with optimal capital structure decisions, indirect costs become of great importance (e.g. business disruption or lost of investment opportunities). Third, Myers discusses that the majority of financing alternatives incur transaction costs which must take a specific form for the analysis to work. For example, applying for loans, firms incur application and start-up fees (Holmes et al., 1994). Consequently, adoption or alteration of financing for the firm is generally not costless. Hence, 'Sticky' financing choices are brought about, where firms have a disincentive to move between financing options.

2.10.2.1. Agency Cost

According to trade-off theory, for each firm there is an optimal capital structure reached by trading off the costs against the benefits of the use of debt and equity. The interest tax shield is the main benefit of using debt, whereas its main cost is the increased probability of bankruptcy especially while using higher levels of debt. However, Myers (2001) states that these are not the only benefits and costs associated with the use of debt and equity. The agency cost is another major cost factor associated with financial distress costs. It plays an important role in better explaining trade-off theory and the justification of a reasonable use of debt which is usually found empirically less than the 100% use of debt.

The agency cost problem has been well described in the work of Jensen and Meckling (1976) and Jensen (1986). These researchers identified a situation ex post asymmetric information associated with conflicts of interests between the different stakeholders of the firm which leads to agency costs.

2.10.2.2. Dynamic Trade-off Theory

The role of time has been disregarded by the basic form of the trade-off theory given that it is a static (one-period) model which implicitly assumes all firms should be at their optimal capital structure at all time (Frank and Goyal, 2007). However, assuming that firms plan their capital structure looking only one period ahead is unrealistic. While taking into account the effect of time on the capital structure planning, this limitation requires a more dynamic theory based on the basic form of trade-off theory (taxation and bankruptcy cost). This requirement of the dynamic trade-off theory indicates that the correct financing decision depends typically on the financing margin anticipated by the firm in the next period. In another word, the optimal capital structure in period t+1 depends on the optimal capital structure in period t+2 which depends on t+3 and so on.

Dynamic trade-off theory was further developed in various respects. For example, Stiglitz (1973) examines the effects of taxation from a public finance perspective. Brennan and Schwartz (1984) investigate the trade-off between tax savings and bankruptcy cost while using continuous time models with uncertainty, taxes, and bankruptcy costs. Based on the idea that firms react to adverse shocks immediately by rebalancing costlessly, they find that in order to take advantage of the tax savings, firms sustain high levels of debt.

According to Goldstein et al. (2001), dynamic trade-off theory can also be used to consider the option values embedded in deferring leverage decisions to the next period. They find that some firms tend to use low levels of debt in order to be able to increase them in the future. In other words, their argument suggests that reduced debt levels today help in attaining the optimal debt level in the future. In line with the assumption of Goldstein et al. (2001), Strebulaev (2007) observes that debt levels in most firms differ substantially from the optimal level most of the time with firms' optimally financing only periodically because of transaction costs. He concludes that firms react better to long-run equity fluctuations rather than short-run changes.

Dynamic trade-off theory has changed my understanding of mean reversion, the role of retained earnings, and the role of profit(Luigi and Sorin, 2009). However, the empirical studies in the literature are fairly recent so any generalisation on the results may be tentative.

2.10.2.3. Empirical Findings from the Trade-off Theory

Conducting an empirical study testing trade-off theory is considered fairly difficult. However, since the introduction of this theory, many researchers have tried to test this theory in different ways. For example, in order to provide empirical evidence supporting the trade-off theory, a study by Mackie-Mason (1990) finds a negative correlation between the amount of tax loss carried-forward and the amount of new debt issue. Bradley et al. (1984) find that volatility of earnings has an impact on debt levels together with strong industry effects. Other studies have used a “target adjustment model” for testing whether companies, over time, will adjust towards an optimal capital structure. For further support for the trade-off theory see Auerbach (1985) or Jalilvand and Harris (1984) who find and interpret significant adjustment coefficients as support for target adjustment behaviour.

Some studies attempt to discover if SMEs behave similarly to large listed companies in terms of the trade-off theory. Some researchers claim that theories usually applied to large listed companies, i.e. trade-off and pecking order, explain the actions taken by SMEs managers regarding financial decisions (Sogorb-Mira, 2005). In the framework of trade-off theory, SMEs will probably face the same trade-off between the interest tax shield and distress costs. Nevertheless, SMEs may stress the importance of certain issues or handle problems that are not faced to the same degree by large listed companies. Some of these issues and the possible implications for the SMEs capital structure will be briefly discussed. Simple lack of knowledge among managers is one possible reason that could explain why SMEs might not follow the trade-off theory. If the financing decision is to be made according to the trade-off theory, it is necessary for managers to be aware of the interest tax shield advantages. Within the SME segment, it is expected that many companies are led by entrepreneurs whose expert skills lies within a field different from finance, therefore,, they might not take advantage of the interest tax shield because of their ignorance of it (OECD, 2006). Unaware of the benefits of leverage, managers might tend to operate at lower debt levels. The potential financial constraints on SMEs are another relevant factor. If SMEs are financially constrained it means that independently of whether managers are aware of the trade-off theory and recognize the advantage of debt, they might not have the ability to lever up to their optimal capital structure. This notion becomes an important issue since, in terms of the trade-off theory; it implies that for external reasons, SMEs might not have sufficient debt. Serious consequences may be imagined if the lack of debt-financing restricts growth in the company by making it necessary to pass up profitable investment opportunities. Lack of debt-financing does not necessarily signify that financing is unavailable; it can also mean that the price of the available finance is prohibitive.

To conclude, often being family owned, SMEs have higher bankruptcy costs; as a result, SMEs' capital structure is different from their large listed counterparts. Besides the expected financial distress costs and the economic loss due to bankruptcy, a family held company probably has a great sentimental value to its owners. Thus, an argument that might be taken into consideration suggests that this dimension of distress costs will increase the expected costs of debt and thus lower the optimal capital structure of family owned companies. Conveniently, within the framework of trade-off theory, this explains the probable deviation of SMEs capital structure from that of large listed companies.

2.10.3. Pecking Order Theory

In a survey study among American firms, Donaldson (1961) first introduced the pecking order theory, later developed by Myers (1984) and Myers and Majluf (1984), which, as a starting point, suggested an alternative approach to the optimal capital structure. This theory states that internal financing (as retained earnings or excess liquid assets) is preferable to external finance by firms. If internal funds are insufficient, firms will turn to different external finance sources starting with debt financing followed by hybrid instruments, and as a last resort issue equity. Myers (1984) argues that in this way of financing, there is no optimal debt-ratio and firms do not attempt to attain target leverage and; instead, their need for external finance becomes the determining factor of the capital structure mix (debt and equity financing).

The rationale behind this theory is that managers, who act in the best interest of existing shareholders, have better information about the future prospects of the firm than outside investors. This is known as asymmetry of information between insiders (e.g. managers) and outsiders (investors). Due to these information asymmetries, potential investors perceive any stock issuance as a bad signal as they assume that managers issue stock only when overvalued which leads to a reduction in the share price. Therefore, Myers and Majluf (1984) predict that following a pecking order, by using up internal funds first, becomes a necessity for managers in need of funds and seeking to avoid this adverse signalling problem. Once internal funds are exhausted, debt will be preferred to equity as it is less susceptible to undervaluation due to information asymmetries. They further discuss that in the absence of investment opportunities, firms, by retaining profits, tend to build up financial slack in order to avoid the future need to raising external finance.

2.10.3.1. Empirical Findings from the Pecking Order Theory

The empirical literature on the pecking order theory provides inconclusive findings about its validity. The works of Shyam-Sunder and Myers (1999), Titman and Wessels (1988), Fama and French (2002), and Frank and Goyal (2003) find evidence supportive of the pecking order theory. These studies confirm the pecking order behaviour through realizing a negative correlation between profits and debt. On the other hand, Fama and French (2005) reconsider their paper in 2002 trying to critically answer when and how often firms issue equity. Their conclusions illustrate that 54% to 72% of their sample makes net equity issues yearly. In their sample, more than half of the firms violate the pecking order behaviour. Additionally, a study by Galpin (2004) shows the invalidity of the pecking order hypothesis which assumes that debt financing costs are cheaper than equity costs. Compared to equity costs, he observes an increase of debt costs over time. In 1973, the debt costs amounted to 50% of equity costs, and increased to reach 140% in 2002.

The SMEs literature offers studies trying to verify the validity of the pecking order theory within SMEs context and aims to explain the two main reasons behind firms following the pecking order theory preferring (a) internal sources of funding over external funds, and (b) risky debt over equity issuance.

The first reason can be summarised by demand-side explanations that are based on the well-established fact that SME owners are extremely reluctant to relinquish control of their business (e.g. (Bolton, 1971; LeCornu et al., 1996)). SME owners attempt to meet their financing needs from a pecking order, sequentially of, their "own" money (personal savings and retained earnings), short-term borrowings, longer term debt, and finally introducing new equity to investors (Cosh and Hughes, 1994). In accordance with Myers (1984), over an extended period, the observed debt ratios will reflect the cumulative need for external finance and vary between both industries and firms in the same industry. Some researchers suggest empirical evidence assuming that the pecking order theory, or an adapted version of it, explicates capital structure choice in SMEs (Holmes and Kent, 1991; Zoppa and McMahon, 2002; Watson and Wilson, 2002; Berggren et al., 2000; Hogan and Hutson, 2005).

The second reason is based on the supply-side constraints that exist when SMEs require debt financing at market interest rates, yet cannot obtain such finance leading to undercapitalisation (Stiglitz and Weiss, 1981). This is regarded as an underinvestment problem where equity clears the market. The existence of such a funding gap has not yet been supported by conclusive empirical evidence. Some commentators do not consider that all SMEs have experienced the funding gap despite the fact that it affects certain firms in particular age and industry categories. The evidence presented by Cressy and Olofsson (1997) suggests that in some European countries the gaps are confined to specific financing modes (debt or equity) and to specific sectors or types of firm (e.g. Hitech) (Moore, 1993), plus, they possibly will be a function of the economy state (recession or boom) (Hughes, 1997). Variables such as asset structure (Cressy and Olofsson, 1997), firm size (Chittenden et al., 1996), lending institutions (Cassar and Holmes, 2003), gross sales (Romano et al., 2001) have been highlighted, by previous studies, as important factors to the capital structure decisions of the firm.

2.10.4. Market Timing Theory

The idea of market timing theory is that equity issuing will depend on market performance (Korajczyk et al., 1991). According to the theory, firms will issue equity when stock prices are high and repurchase them when the prices are low. The idea is to take advantage of temporary fluctuation in the cost of equity comparing it with other forms of capital. In the perfect market assumption of Modigliani and Miller (1958) there is no difference between debt and equity financing. However, in an inefficient capital market, market timing can benefit both shareholders and firms.

Baker and Wurgler (2002) were the first to find a theoretical and empirical relationship between firms’ capital structure and market timing theory. They test the relationship by using market to book value as a proxy of firm’s valuation. They state that equity should be issued when the shares prices are overvalued and shares should be repurchased when the prices are undervalued. Thus, market timing theory assumption is that when market value, measured relative to book value, is high firms prefer equity rather than debt because there is overvaluation in the market. Overvaluation of the firms’ stocks can be a result of investors being overoptimistic about the firms’ expected return. On the other hand, when investors are pessimistic about firms’ expected return the stock prices will be undervalued. Firms try to time the market to take advantage of market mispricing and issue equity.

2.10.4.1. Empirical Findings from the Market Timing Theory

The empirical literature on market timing theory provides inconclusive findings about its validity. One of the critical points raised against this theory is the persistence of capital structure, whether it could be long term or not. The results of Baker and Wurgler (2002) successfully demonstrated the persistent effect of equity issuance. If the persistence is still there then the company does not need to rush to adjus leverage.

Bougatef and Chichti (2010) investigate the persistence of equity market timing attempts on capital structures of Tunisian and French firms and find that high market-to-book ratios are associated with high equity issues. Tunisian and French firms take advantage of market timing theory to raise capital. They issue equity when their market valuations are higher than their book values and after an improvement of market performance and take advantage of temporary overvaluation by issuing equity. These findings are consistent with the market timing theory.

De Bie and De Haan (2004) examine the effects of market timing on capital structures of Dutch firms using Kayhan and Titman’s (2007) methodology during 1983-1997 and find only weak evidence of market timing effects on capital structures of Dutch companies. Firms issue relatively more equity after periods of stock price increases.

Hovakimian (2006) finds that the importance of historical average market-to-book in leverage regressions is not due to past equity market timing. He finds that equity issues may be timed according to conditions in equity market, but the conditions do not have significant long-lasting effects on capital structure. Cai and Zhang'S (2006) findings are not consistent with the market timing hypothesis in a study of U.S public firms during 1975-2002.

2.11. Conclusion

This chapter is broadly divided into three key topics. The first topic attempts to shed some light on the credit risk modelling literature review. It starts with a general introduction about credit risk modelling and introduces the two worlds of credit risk mainly spread and default risk. Moreover, this chapter provides a critical literature review on the three dominant approaches of default risk models, namely, (i) traditional models which are based mainly on accounting information while using linear discriminant analysis (e.g. Altman (1968)), (ii) contingent claims-based (CCB) models that view equity as a call option on assets (Merton,1974; Bharath and Shumway, 2008), and (iii) survival analysis models (also known as hazard models) which have the ability to assess failure risk using both accounting and market information while incorporating the time to failure in the prediction probability (Shumway, 2001). The second key topic discusses the main literature on the relationship between the Basel Accords and SMEs and covers the following aspects: (i) the development of the Basel Accords, (ii) Basel Accords and lending to SMEs, (iii) bank capital requirements for SMEs. In addition, it highlights the important literature on the two types of relationship between banks and SMEs, namely, relationship lending and transactional lending. Finally, the third key topic provides a summary literature review of capital structure theories. These theories are classified into four main theories, namely, the Modigliani-Miller theorem, the trade-off theory, the pecking order theory, and the signalling theory.

Chapter Three

3. The effect of size on the failure probabilities of SMEs: An empirical study on the US market using discrete hazard model

3.1. Introduction

Small and medium-sized enterprises (SMEs) are viewed as the backbone of the economy of many countries all over the world since they are the incubators of employment, growth, and innovation (Altman and Sabato, 2007). SMEs constantly play a vital role in the US economy where statistics from the "US Small Business Administration[7]" show that small businesses make up 99.7% of US employer firms in 2011, and they accounted for 63% of the new jobs created between 1993 and 2013. These numbers emphasize on the importance of SMEs as job creation engines; Furthermore, the Bureau of Labour Statistics[8] and a study by the economist intelligence unit in 2009 show that during the financial crises SMEs continued to hire employees and create new job opportunities (Economist intelligence Unit, 2009).

The introduction of the new Basel Capital accord and the global financial crises of 2007 opened the door for more in-depth and adequate research on failure[9] prediction models for all firms. However, the financial distress definition of Basel II, 90 days overdue on credit agreement payments, which are considered as the operational definition, failed to distinguish between large and small firms which have different structures from the credit risk point of view (Dietsch and Petey, 2004; and Altman and Sabato, 2007).

[7] Small Business Administration known as "SBA" was created in 1953 as an independent agency of the federal government to aid, counsel, assist and protect the interests of small businesses in the US. For more details: http://www.sba.gov/

[8] Source: Bureau of Labour Statistics, BED. For the latest employment statistics, see Advocacy's quarterly reports, www.sba.gov/advocacy/10871.

[9] The terms failure, bankruptcy, default, and insolvency are used interchangeably in this paper.

Credit risk modelling for large, listed firms is extensive and gravitates towards two approaches: The Altman (1968) approach which uses historical accounting data to predict bankruptcy; and the Merton (1974) approach which relies on securities market information.

More recently, banks and financial institutions started to realize the importance of distinguishing SMEs from large firms while modelling for credit risk since they require specific risk management tools and methodologies to be developed for them (Altman et al., 2010). In line with this, Dietsch and Petey (2004) argue that German and French SMEs are riskier than large firms but have lower asset correlation with each other. Altman and Sabato (2007) provide a distress prediction model specifically designed for the US SMEs sector based on a set of financial ratios derived from accounting information.

In recent years a new trend of literature started to focus on the diversity within the SMEs category dividing the SMEs into micro, small, and medium sized firms. These categories are classified in terms of the firms' management style (Wager, 1998), access to finance (Beck et al., 2006), number of employees (Gupta et al., 2014) etc. However, a limited literature in this area has been devoted to study the credit risk behaviour of these different categories (see for example, Gupta et al. (2014)). In my study I will address this research gap by classifying SMEs into three distinct categories (micro, small, and medium) while developing a bankruptcy prediction model using a set of financial ratios. I will apply the discrete-time duration-dependant hazard rate modelling technique to develop separate bankruptcy prediction models for each of the three categories.

The main contribution of this paper is to investigate the extent to which the size affects the SMEs probabilities of bankruptcy while dividing my sample into three main size segments namely micro, small, and medium. In addition, I forecast the bankruptcy probabilities by developing discrete-time duration-dependant hazard models. My paper is a continuation and improvement of three papers in the literature of SMEs failure: Altman and Sabato (2007), Holmes et al. (2010), and Gupta et al. (2014). I differ from Altman and Sabato's (2007) paper in two ways. Firstly, I am further classifying SMEs into three categories (micro, small, and medium) while modelling for bankruptcy prediction. In this study I will try to capture any differences that exist between these categories and to what extent this might help lenders to further assess their credit models. Secondly, I utilize a more recent sample period (in and out of sample) which includes the recent financial crises in 2007; by this I assess the extent to which the financial crises affected the SMEs sector and the bankruptcy prediction model of SME firms. Holmes et al. (2010) study the survival of SMEs for the period from 1973 till 2001 and separate between micro firms and small and medium firms using hazard model methodology. They find that each segment is differently affected by firm-specific and macro-economic factors. However, the data used in their study differs from my data, where they have concentrated their sample on a specific geographical location within the UK (North-East England) and they limited their sample only to a specific industrial segment which is the manufacturing sector and this sector represents only 12% of the UK firms. Moreover, they have not used any financial information in their analysis covering a too wide and back dated sampling period. In regard to Gupta et al.'s (2014) paper, I differ from it in several ways. First, I test the SMEs categories on a geographically different sample (US firms) and in doing so I emphasize the substantial soundness and significance of distinguishing between the broad SMEs categories. Second, from a methodological point of view, while applying discreet hazard models, the estimation of baseline hazard should be done using time dummies (Beck et al., 1998) or some other functional form of time (Jenkins, 2005). However, Gupta et al. (2014) have created the baseline hazard while including insolvency risk variable which distort the idea of baseline hazard. Moreover, they have utilized the ROC curve as their out of sample validation technique, however, this technique has been criticized by many scholars. In this study, I have applied certain improvements to their paper by establishing a more precise baseline hazard function based on time dummies and applied an out of sample evaluation technique similar to the one used by Shumway (2001) which provides more accurate results.

The analysis is carried out on a sample of 11,117 US non-financial firms from which 465 are defaulted firms, spanning the time period from 1980 till 2013. My empirical findings show that significant differences exist between the bankruptcy attributes of micro and small firms on one hand and SMEs firms on the other. Therefore, a separate treatment should be provided while modelling for the credit risks of these categories. Moreover, I find similar results to that found by Gupta et al. (2014) that the explanatory power of financial reports increases with the size of the firms. I find that medium and the whole sample of SMEs bankruptcy attributes have almost an identical set of explanatory power leading us to believe that there is no material impact on the decision making process between these two groups unlike the micro and small SMEs. Finally, I have provided an out of sample validation following the Shumway (2001) measure, my out of sample results show good performance classifications for the four bankruptcy prediction models developed.

The remainder of the chapter proceeds as follows. Section 3.2 provides an overview on the literature review of the studies conducted on micro, small, and medium-sized enterprises. Section 3.3 provides an explanation about the source of the data used, the statistical method utilized in this research, and the selection of covariates included in this study. Section 3.4 presents the key descriptive statistics for the covariates used and their correlation matrix, Univariate analysis is applied and the development of the discrete-time duration-dependant hazard models estimated for each of the SMEs segments.

3.2. Literature Review

Research on small and medium-sized enterprises has gained a lot of attention and covered a wide range of issues in the previous decade. Micro, small and medium-sized enterprises (SMEs) are the engine of the economy. They are an essential source of jobs and create entrepreneurial spirit and innovation and are thus crucial for fostering competitiveness and employment. In 2005 a new definition from the EU came into force further classifying SMEs into three categories namely, micro, small, and medium enterprises. A firm is defined as ‘micro’ if it has less than 10 employees and an annual turnover of under €2 million; ‘small’ if it has less than 50 employees with an annual turnover of less than €10 million, and ‘medium’ if it has less than 250 employees with an annual turnover of less than €50 million. Since my paper aims to analyse the US market, I partially adopt these definitions and try to fit them within the SBA definition for SMEs in the US relying on the number of employees as the main factor of classification. Therefore, I will define a firm as ‘micro’ if it has less than 20 employees; ‘small’ if it has less than 100 employees; and ‘medium’ if it has less than 500 employees.

The empirical literature on SMEs has been extensively investigated especially after the new Basel Accord for bank capital adequacy (Basel II) (see for example Altman and Sabato (2005) and Berger (2006)). These studies covered a broad area of SMEs literature such as understanding the capital structure determinants of SMEs (Sogorb-Mira, 2005), investigating the key drivers of SME profitability and riskiness for US banks (Kolari and Shin, 2004) and the lending structure and strategies (Berger and Udell, 2004) etc.

Despite all these studies, a limited number of research studies have tried to further understand the sub-categories of SMEs and whether each category enjoys a unique set of characteristics. These studies investigate a broad dimension of research and report differences within the SMEs sectors.

A study of the personnel management dimension within the SMEs conducted by Kotey and Slade (2005) show that differences exists between micro, small, and medium Australian firms. Their paper reports that the rate of adoption of formal human resources management practices increases with firm size. The results reported demonstrate a move toward division of labour, hierarchical structures, increased documentation, and more administrative processes as the number of employees increase. In addition, they advise taking into account the diversity of practices associated with various firm sizes and providing consultation and management training to SMEs personnel.

Another study by De Mel et al. (2009) focused on the innovation dimension within the different categories of SMEs. They report that more than one quarter of microenterprises are found to be engaging in innovation, with marketing innovations the most common, and firm size is found to have a stronger positive effect, and competition a stronger negative effect, on process and organizational innovations than on product innovations. Beck et al. (2005) investigate the effect of firm size on the extent to which the corruption of bank officials and financial and legal issue constrain a firm's growth. They found that the smaller the firm the more it is affected by these constrains.

Besides differences in personnel management, innovation, and corruption, Beck et al. (2006) find that accessing to finance also depends on the firm size, where they find that the larger the firm size the less access to finance is seen as a problem. They report that the probability a firm rates financing as a major obstacle toward its growth is 39% for small, 38% for medium, and 29% for large firms.

With regard to leverage decisions and capital structure, Ramalho and Da Silva (2009) conduct a study on Portuguese SMEs and show that different size structure (micro, small, medium, and large) affect significantly the determinants of leverage decisions. The other research by Mateev et al. (2003) tries to explore the capital structure choices for each of the SMEs categories. They find that medium-sized firms are mainly dependant on long term bank loans as their preferred method of external financing, while short-term loans and trade credits are the main source of external financing for both micro and small firms.

Recently, more attention has been given to the effect of SMEs categories on default probabilities and to what extent does firm size matter in prediction of default. Empirical literature argue that the larger the firm is the more stable cash flow it holds and the more diversified it is (Gill et al., 2009) leading to a negative relationship between firm size and default probabilities (Pettit and Singer, 1985). A recent study by Gupta et al. (2014) investigates the financial and non-financial factors that influence the failure within each of the SME categories (micro, small, and medium). Their findings provide strong evidence that the credit risk characteristics of firms within the broad SMEs segment do vary suggesting a separate treatment for each of the categories to get a better pricing of credit risk.

3.3. Empirical Analysis

This section provides detailed explanation about the source of the data used, the statistical methods utilized in this research, and the selection of covariates included in this study.

3.3.1. Data

My empirical analysis is performed using panel data available to us from the Compustat database. The sample employs annual firm-level accounting data for 465 bankrupt and 10,652 non-bankrupt US small and medium-sized enterprises having less than 500 employees and an average annual receipts of less than $ 7.5 million, covering an analysis period from 1980 till 2013. Furthermore, to validate the out-of-sample prediction performance of the models developed the entire study window is divided into two groups: the estimation period (1980-2008, 28 years) for the model building and the forecasting period (2009-2013, 5 years) for the out-of-sample forecasting performance test. As discussed above, the SBA has established a widely used size standard to define SMEs of 500 employees and annual turnover receipts of $ 7.5 million for most industries. Moreover, the SMEs can be further classified into sub-samples of micro, small, and medium firms. The micro firms consists of less than 20 employees; firms are classified as “Small” if they have greater than or equal to 20 but less than 100; and “Medium” firms if they have greater than or equal to 100 and less than 500 employees. Further details regarding to the sub-samples are reported in table 3.1. It is important to mention that these definitions differ from the European Union ones which classify firms with only less than 250 employees as SMEs and which are used in different studies such as Altman et al. (2010). Using my classifications, 213 failed micro firms are reported constituting around 46% of the total bankrupt SMEs sample compared to 115 failed firms for small SMEs and 137 failed firms for medium SMEs contributing 25% and 29% of the total bankrupt SMEs sample respectively.

Table 3.1 the composition of the sample of Bankrupt and Healthy firms
This table shows the number and the percentage of total sample of bankrupt and healthy SMEs for each year throughout the sample period.

Year	Bankrupt firms	% of Total sample	Healthy firm	% of total sample	Total Sample
1980	15	1.98	743	98.02	758
1981	4	0.98	403	99.02	407
1982	7	1.67	413	98.33	420
1983	15	3.59	403	96.41	418
1984	12	2.95	395	97.05	407
1985	13	2.73	463	97.27	476
1986	21	4.31	466	95.69	487
1987	18	4.74	362	95.26	380
1988	11	3.78	280	96.22	291
1989	20	7.69	240	92.31	260
1990	17	6.88	230	93.12	247
1991	24	6.82	328	93.18	352
1992	13	4.04	309	95.96	322
1993	23	5.42	401	94.58	424
1994	21	5.13	388	94.87	409
1995	19	3.91	467	96.09	486
1996	18	3.44	505	96.56	523
1997	23	6.12	353	93.88	376
1998	26	8.67	274	91.33	300
1999	17	2.96	558	97.04	575
2000	13	3.07	411	96.93	424
2001	19	7.79	225	92.21	244
2002	11	7.01	146	92.99	157
2003	14	6.97	187	93.03	201
2004	9	7.26	115	92.74	124
2005	13	8.50	140	91.50	153
2006	9	5.36	159	94.64	168
2007	4	2.31	169	97.69	173
2008	8	6.06	124	93.94	132
2009	10	6.37	147	93.63	157
2010	6	3.17	183	96.83	189
2011	4	1.95	201	98.05	205
2012	5	1.84	267	98.16	272
2013	3	1.50	197	98.50	200
Total	465	4.18	10652	95.82	11117

Table 3.2 the distribution of US dataset across SMEs segments
The table shows the sub-classification of my database among micro, small, and medium SMEs, in addition to their default rate percentage.

Firm Category	Failed	Healthy	Total	Failed/Total %
SMEs	465	10652	11117	4.18
Micro	213	2638	2851	7.47
Small	115	3389	3504	3.28
Medium	137	4625	4762	2.88

In this study, I will consider firms to have failed only if they filed for legal bankruptcy proceedings (both Chapter 11 and 7) within the time period studied. Firms are classified to be legally bankrupt in Compustat database if the company has "TL" footnote on the status alert (Data item STALT) indicating that the firm is in bankruptcy or liquidation (e.g. Chapter 7/11). Furthermore, in line with other studies such as Altman et al. (2010) I exclude financial, insurance, and utility firms from my sample. The firms eliminated have industrial classification (SIC) codes from 6000 through 6999 for financial firms and 4900 through 4949 for regulated utilities. Finally, I will control for macroeconomic effects by including the change in annual interest rates in the US throughout the period of my sample. This macroeconomic variable has been suggested by Hillegeist et al. (2001) as a control for macroeconomic conditions affecting the firm's default probabilities. In addition, I control for industry effects by classifying the firms into nine distinctive categories according to the SIC codes and including the variable as a factorial variable. Extreme outliers have been eliminated so that my models are not heavily influenced by them, I winsorised all my financial ratios between 5th and 95th percentiles. In addition, I have lagged all the covariates by one-time period so that all information is available in the beginning of the relevant time period.

Table 3.3 industry code construction
This table gives the SIC codes unique industry codes from 1 to 9 along with the name of each industry. The last column gives the number of bankruptcies during the sample period 1980 - 2013 in each of these industries.

IND Code	SIC code	Industry name	Number of bankruptcies	% of Bankruptcies
1	<1000	Agriculture, Forestry and Fisheries	7	1.51%
2	1000 to less than 1500	Mineral Industries	36	7.74%
3	1500 to less than 1800	Construction Industries	14	3.01%
4	2000 to less than 4000	Manufacturing	186	40.00%
5	4000 to less than 4899	Transportation and Communications	36	7.74%
6	4950 to less than 5200	Wholesale Trade	28	6.02%
7	5200 to less than 6000	Retail Trade	40	8.60%
8	7000 to less than 8900	Service Industries	53	11.40%
9	9100 to less than 10000	Public Administration	65	13.98%
		Total # of Bankruptcies	465	100.00%

3.3.2. Discrete-Time Duration-Dependant Hazard Model

3.3.2.1.The Hazard Model

In his seminal work Shumway (2001) argues that the static models such as multiple discriminant analysis (MDA) and ordinary single-period logit techniques are inappropriate for default prediction due to the characteristics of bankruptcy data. The underlying characteristics for the majority of firms evolve over time but static models allow only for a single firm-year observation for each non-failed firm that is randomly drawn from the used data-set, while, for failed firms the firm-year observation immediately preceding the bankruptcy filing year is selected on a non-random basis leading to a possible sample selection bias (Hillegeist et al. 2004). Moreover, the single-period logit technique leads to understated values of standard errors (Beck et al. 1998), and fails to capture time-varying changes in the explanatory variable (Hillegeist et al. 2004). Therefore, researchers proposed new techniques to overcome the problems associated with static models. Hwang et al (2007) propose a robust semi-parametric logit model with smaller hold-out sample error rates. Whereas, Kukuk and Ronnberg (2013) suggest a mixed logit model which extends the normal logit model by allowing for varying stochastic parameters and non-linearity of covariates. Furthermore, Shumway (2001) suggests the utilization of hazard models in predicting bankruptcy probabilities where these models should be specified as duration dependant models with time-varying covariates. He highlights three reasons why the hazard model should be preferred over the static model: (i) the failure of the static logit to account for each firm's period at risk, (ii) the incorporation of time-varying explanatory variables, (iii) hazard models enjoy a higher predictive power in their out-of-sample test. Recent studies compare Shumway model with other static models and show better forecasting performance of hazard models (see among others Chava and Jarrow (2004); and Bauer and Agarwal (2014)).

Furthermore, Hwang (2012) reports superior performance using discrete-time duration-dependant hazard rate over the discrete-time hazard model without time-varying specification.

Nam et al. (2008) also argue that the discrete-time duration-dependant hazard model can be equivalent to a panel logistic model that incorporates macro-dependant base-line hazard.

The conditional probability of discrete time hazard function (λ) for firm i to default in the time interval t, given it survives up to this time interval is as follows:

$$\lambda\left(t \backslash X_{i,t}\right) = Pr(T = t \backslash T \geq t, X_{i,t}) \qquad (1)$$

T is discrete failure time; T = t states failure within the time interval t and $X_{i,t}$ is the value of covariates of firm i up to time interval t, whereas the hazard model can be expressed in the following equation:

$$h(t \backslash X_{i,t}) = h(t \backslash 0) \, . \exp\{X_{i,t}\beta\} \qquad (2)$$

Where, $h(t \backslash X_{i,t})$ is the individual hazard rate of firm i at time t, $h(t \backslash 0)$ is the baseline hazard rate and $X_{i,t}$ is the vector of covariates of each company i at time t.

The discrete hazard technique fits well with the characteristics of the bankruptcy data utilized since it is consistent with the binary dependant variables and enjoy both time-series and cross-sectional characteristics. Furthermore, in line with the previous literature discussed and to avoid the limitation of other statistical techniques I estimate my hazard models in a discrete-time framework with random effects thus controlling for unobserved heterogeneity and shared frailty. The final equation used in this paper will take the following form, where a(t) is the time-varying covariate introduced to capture the baseline hazard rate and $P_{i,t}$ is the probability of experiencing the event by firm i at time t.

$$P_{i,t} = \frac{e^{\alpha(t)+ \beta X_{i,t}}}{1+ e^{\alpha(t)+ \beta X_{i,t}}} \qquad (3)$$

3.3.2.2.Specification of the Baseline Hazard Rate

There are several ways to proxy the baseline hazard function a(t), when all the covariates are equal to zero, depending on the definition of the time-varying covariates that have functional relationships with survival times. The first method is the log (survival time) which has been applied by Shumway (2001) who used a time-invariant constant term, ln (Age). This is used for duration-independent models where the baseline hazard rate is assumed to be a constant term. In this case, the individual hazard rate, $h(t \backslash X_{i,t})$ for firm i will be independent of the particular point of time or the survival period. The second method employs time dummies as a proxy for the baseline hazard rate. This method is utilized for duration-dependant models where the baseline hazard is assumed to be time-varying. Beck et al (1998) uses this method in their work, where the baseline hazard term, a_t , is a dummy variable marking the length of the sequence of zeroes that precede the current observation. For example if the maximum survival time is sixty four year, then sixty three dummy variables are required for model estimation[10]. Finally, an alternative method to specify the baseline hazard rate is to use the piece-wise constant method. According to Jenkins (2005) this method splits the survival times into different time intervals that are each assumed to exhibit constant hazard rates. Overall, the choice of method depends on the shape of the hazard curve where frequent and continuous rises and falls suggest the use of fully non-parametric baseline hazard estimation.

Recently, some studies have moved away from baseline hazard estimation using time dummies by establishing other versions of baseline hazard that incorporates different types of variables. According to Nam et al (2008), indirect measures like time dummies are less effective in capturing time-varying macro dependences. Therefore, many researchers propose direct measures to estimate the baseline hazard rate. For example, Hillegeist et al (2001) propose the use of two direct measures; the rate of recent defaults and changes in interest rates. Nam et al (2008) use changes in interest rates and volatility of foreign exchange rates, whereas Altman et al (2010) and Gupta et al. (2014) construct industry “weight of evidence” variables.

3.3.2.3.Performance Evaluation

In order to examine the effectiveness of the models developed for the perdition of SMEs bankruptcy I perform a bankruptcy out-of-sample prediction test similar to Shumway (2001). I specify my out-of-sample period to be from 2009 to 2013. Therefore, I re-calculate all the forecasting models for the period from 1980 till 2008 and then year by year I rank the firms into deciles based on their computed bankruptcy probabilities. The firms most likely to default in the subsequent year are placed into the first decile, the next most likely to default in the second decile, and so on. Subsequently, I report for each decile the percentage of firms that defaulted. The model is considered to enjoy

[10] The model is run using sixty three years rather than sixty four dummies in order not to fall in the multicollinearity trap.

better classification performance the higher the percentage of firms that experience default in the top deciles.

3.3.3. Selection of Covariates

A considerable number of ratios have been tested and used in the literature to predict SMEs default risk. Chen and Shimerda (1981) state that out of more than 100 financial ratios, almost 50% were found useful in at least one empirical study. This study focuses on the role of accounting ratios on the probability of SMEs failure. Therefore, the variables are selected from five broad categories that capture the firm's performance in the dimensions of profitability, leverage, activity, solvency, and liquidity. For each of these categories, I add a number of financial ratios that have previously been shown to be effective in predicting SMEs insolvency risk.

In order to select the most appropriate ratios for my final multivariate model, I apply two tests for each of the 20 financial ratios distributed over the five categories. Table 3.9 presents the competing covariates that will be included in the univariate tests. The first step in choosing among these ratios is the implementation of a univariate regression analysis. This univariate test provides us with an initial understanding of the discriminate power of the explanatory variables (Nam et al. (2008); Altman et al. (2010)). I keep all the ratios that show significant explanatory power and enjoy the expected sign relative to the dependant variable which is in my case the probability of default. For the selected ratios I run a correlation test to identify any high correlations between these ratios. When ratios within each group exhibit high correlation, the covariates with lower chi-square values will be dropped from the final multivariate model since that indicates lower explanatory power for those ratios.

3.4. Results and Discussion

In this section I perform a univariate analysis of each individual covariate in my broad list of ratios followed by a correlation test. Furthermore, an analysis of key measures of descriptive statistics of the final selected explanatory variables is presented. Then I illustrate the process of developing my multivariate models for each SMEs category and for the SMEs as a whole. Thus allows us to compare and highlight the main differences between the models. Finally, I discuss the development of my out of sample classification performance for the models developed.

3.4.1. Univariate Analysis and Correlation Matrix

In this section univariate analysis is provided before proceeding to the development of the final multivariate models. Univariate analysis has been widely recommended and used in the literature to obtain an initial understanding about the discriminate power of the explanatory variables (Nam et al. (2008) and Altman et al. (2010)). Usually, the standard approach in survival analysis is to obtain an insight about the shape of survival functions through the estimation of Kaplan-Meier survival curves for all categorical variables (Cleves et al., 2010). In addition, non-parametric tests such as log-rank and Wilcoxon-Breslow-Gehan tests are widely used to test the equality of survival functions for these categorical predictors (Cleves et al., 2010). However, the use of these tests may lead to biased discriminatory results if they have been applied on continuous predictors such as the case of my independent continuous variables[11]. So, to avoid any biased results univariate analysis will be conducted. The results of the univariate regressions are reported in table 3.4.

To select the set of covariates that enter my multivariate model I choose those covariates that enjoy the expected sign while displaying significant discriminatory

[11] See for example http://www.ats.ucla.edu/STAT/stata/seminars/stata_survival/default.htm. Also see Cleves *et al.* (2010) for a more thorough understanding.

power when estimated using the discrete-hazard model for the different SMEs segments. An initial overview on table 3.4 indicates that within the profitability ratios all of the covariates, except for NISALE, RETA, and NITE have a significant discriminatory power and all those covariates show the expected sign compared to the dependant variable. However, among the leverage ratios, STDEBV and TDTA do not show the expected sign, at a significant level, relative to the probability of failure for all the three SMEs segments. Therefore, those two covariates are not considered during the next step. Regarding the remaining three ratio categories each of CG, WCSALE, CSIS, QCACL and CSIAT are not further considered in the correlation process because they do not provide enough statistical significance. Finally, after analysing the univariate regression for each covariate, the following covariates are tested to detect any multicollinearity, EBIDTAIE, EBIDTATA, NITA, XINTTA, CLTA, TCTA, TLTA, CETL, CASALE, TTA, WCTA, and CACL.

The correlation matrix is presented in table 3.5 providing details about the collinearity level among the selected covariates. Out of the twelve covariates, the highest correlations can be found between EBIDTATA and NITA of about 0.9104, CACL and CETL 0.8314, CACL and WCTA 0.7789, TLTA and WCTA -0.7577. A number of other covariates also have a substantial degree of correlation such as XINTTA and TLTA 0.6936 and CETL and CLTA -0.6728. Some of the covariates have to be dropped from my final multivariate model due to the high correlations that exist between them. When two covariates are highly correlated with each other I keep the covariate that enjoys higher Wald chi-square value obtained from the univariate test table. Therefore, I determine seven covariates to enter the multivariate models namely, EBIDTAIE, NITA, TLTA, TCTA, CASALE, TTA, and WCTA.

Table 3.4 univariate analysis
This table reports the coefficients obtained from univariate regression analysis of respective covariates for different SMEs segments. For each size segment the coefficients estimated using discrete-time duration-dependant hazard function. ***, **, * indicates that the coefficient is significant at the 1%, 5%, and 10% respectively.

Ratio	A Priori	SMEs		Micro		Small		Medium	
		β	Chi^2	β	Chi^2	β	Chi^2	β	Chi^2
Profitability									
EBIDTAIE	(-)	-.0108494***	22.07***	-.063638***	13.09***	-.040803***	10.83***	-.022254***	21.75***
EBIDTATA	(-)	-1.19361***	19.50***	-.4889101***	4.72***	-.7048448***	4.75***	-2.107552***	27.01***
NISALE	(-)	-.2319702***	22.34***	-.1565969***	5.27***	-.0593781	0.39	-.2997896***	4.97***
RETA	(-)	-.1839748***	100.92***	-.0230958	0.90	-.0152018	0.12	-.3237676***	31.43***
NITA	(-)	-1.177601***	97.26***	-1.101897***	23.37***	-1.061895***	18.52***	-2.552399***	75.71***
NITE	(-)	.0511206	0.58	.0544052	0.34	.1791202	1.55	-.1472788	1.11
Leverage									
XINTTA	(+)	18.77527***	174.76***	6.154547***	10.07***	21.7166***	55.38***	36.05052***	121.76****
CLTA	(+)	2.587964***	196.91***	.8571542***	12.31***	2.504709***	40.24***	5.487994***	145.48***
TCTA	(+)	3.449214***	47.91***	1.690175***	6.46***	1.998587	3.56	5.395494***	21.88***
TLTA	(+)	2.280608***	296.29***	.7880578***	21.61***	2.826424***	97.01***	4.703341***	188.93***
STDEBV	(+)	.2985613	4.60	.098034	0.17	.3659389	1.73	.1431478	0.34
TDTA	(+)	.6552854	3.30	.3326899	0.46	1.955847***	8.03***	2.593609***	11.69***
Activity									
CETL	(-)	-.3459681***	107.01***	-.1571821***	18.95***	-.8830357***	49.42***	-1.592596***	88.91***
CASALE	(-)	-.3063103***	20.64***	-.376093***	18.36***	-.6182409***	14.16***	-1.187548***	20.33***
TTA	(-)	-15.99513***	143.34***	-26.546821***	25.76***	-27.16891***	52.25***	-24.35967***	130.08***
CG	(-)	-.4290882***	45.41***	-.1534083	3.03	-.2201675	3.13	-1.071719***	39.32***
WCSALE	(-)	-1.053956***	88.47***	-.3517744	8.51	-1.186603***	25.97***	-3.96608***	97.55***
CSIS	(-)	-.4340475***	23.30***	-.3558847	10.11	-1.460792***	25.74***	-1.658405***	20.76***
Liquidity									
WCTA	(-)	-2.199152***	197.37***	-1.2612188***	46.63***	-2.480588***	55.98***	-5.438686***	171.54***
CSIAT	(-)	-.7235075***	9.41***	-1.63	2.50	-5.79959***	46.76***	-5.173211***	38.79***
Solvency									
CACL	(-)	-.321967***	96.34***	-.1010271***	6.98***	-.4620135***	33.67***	-1.090778***	80.92***
QCACL	(-)	-.33133***	84.50***	-.1234249***	8.62***	-.1387676	3.55	-1.219197***	68.80***

Table 3.5 correlation matrix
This table lists the correlation matrix among the covariates used. The * indicates that the correlation is significant at the 1%.

Variable	EBIDTAIE	EBIDTATA	CACL	NITA	XINTTA	TLTA	CETL	TTA	CLTA	TCTA	CASALE	WCTA
EBIDTAIE	1											
EBIDTATA	0.5489*	1										
CACL	0.0412*	0.0916*	1									
NITA	0.4787*	0.9104*	0.1902*	1								
XINTTA	-0.1130*	-0.2401*	-0.4404*	-0.3283*	1							
TLTA	-0.1574*	-0.3471*	-0.6374*	-0.4305*	0.6936*	1						
CETL	0.0579*	0.0917*	0.8314*	0.1799*	-0.4925*	-0.7390*	1					
TTA	0.4465*	0.4049*	0.0960*	0.3461*	-0.1689*	-0.1676*	0.0630*	1				
CLTA	-0.1413*	-0.3832*	-0.6458*	-0.4480*	0.5213*	0.8266*	-0.6728*	-0.1324*	1			
TCTA	-0.1045*	-0.3058*	-0.4980*	-0.3429*	0.3504*	0.4871*	-0.5189*	-0.0831*	0.7051*	1		
CASALE	-0.3391*	-0.4079*	0.4832*	-0.2947*	-0.1543*	-0.2187*	0.4098*	-0.1923*	-0.2146*	-0.2422*	1	
WCTA	0.1315*	0.2828*	0.7789*	0.3745*	-0.5500*	-0.7577*	0.6040*	0.1956*	-0.7382*	-0.4937*	0.3055*	1

3.4.2. Descriptive Statistics

A discussion about the descriptive statistics of the covariates used in this study provides us with an initial understanding about any potential biasness and variability that may arise among the variables in the multivariate models. In table 3.6 I report the mean values and standard deviations for each of the three SMEs categories (micro, small, and medium) and for the whole sample separating the healthy and failed firms. A general overview of the descriptive analysis for the covariates selected shows initial evidence of differences among the variables in different SMEs categories which supports my argument that the factors influencing failure probability differs between each segment. For instance, the mean of EBIDTAIE differs among each category particularly between the SMEs which have -4.518 mean value for failed firms and the medium failed firms with mean of 1.601 which might indicate that the profitability in medium failed firms is much higher than other groups. Surprisingly, the profitability of healthy micro and small SMEs have negative profitability ratios compared to healthy medium SMEs who enjoy a positive mean of 10.183.

In addition, the liquidity ratio WCTA among the micro and small failed firms provide negative results of -0.006 and -0.007 respectively, whereas it is positive among their peers in medium SMEs. This leads us to assume a liquidity problem among the micro and small failed firms compared to medium SMEs.

On the other hand, according to economic hypotheses and previous studies such as (Altman and Sabato (2007); Altman et al. (2010) …etc.) I expect higher means in the failed group than for healthy group for the covariates that enjoy a positive relationship with the probability of failure. Not surprisingly, the means of the leverage ratios (TLTA) and (TCTA) for failed firms are higher than that for the firms in the healthy group among all the categories. Similarly lower means are expected for the covariates in the failed groups compared to those in the healthy groups when these covariates are negatively related to failure probability such as EBIDTAIE, NITA, CASALE, TLTA, and WCTA. Generally these expected relationships hold with the exception of that for TLTA.

3.4.3. The Development of the Discrete-Time Duration-Dependant Hazard Models

In this section, I report on four hazard models that have been separately developed for SMEs, micro, small, and medium firms. The first step in this section is the detection of the baseline hazard rate which is the corner stone to further develop the discrete-time duration-dependant hazard models. This is followed by the development and discussion of the final multivariate models for each segment. The dependant variable for each model is a binary choice variable where (1) indicates bankruptcy and (0) indicates non-bankruptcy. The covariates selected to set up the multivariate models are chosen after the consideration of their significance and correlation with other potential variables.

3.4.3.1.Determination of Baseline Hazard Rate

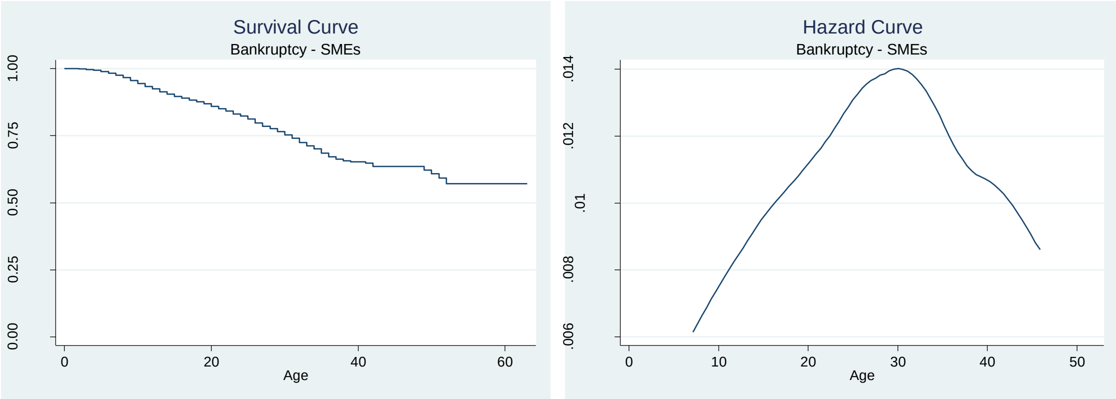
The construction of the baseline hazard rate for these models can be done in different ways as explained in section (3.3.2.). However to choose from these methods the survival and hazard curves most be estimated and analysed. Figure 3.1 provides the estimated curves based on the Kaplan-Meier estimator for the four models separately. The survival probabilities for the whole SMEs model tend towards slightly above 0.50 as the firm age increases towards sixty. However, the survival probability for micro SMEs reduces to below 0.25 when the firms' age touches sixty years. Regarding the survival probability of small SMEs it moves to less than 0.50 when the firms' age approaches sixty years. On the contrary to the small SMEs medium SMEs survival probabilities move in line with the whole SMEs to indicate survival probabilities of just above 0.50 at age 60. The different behaviours of the survival curves for each segment indicate that the survival attributes may be different for each size category. Even though the survival curves give us an initial understanding about the relationship between survival probabilities and the firms' age, it is important to plot the hazard curve for each model in order to decide the most appropriate method of calculating the baseline hazard. From figure 3.1 I can derive that different baseline hazard rate specifications are required for each model since each hazard curve exhibits a different functional relationship with firms' age. Moreover, since all the hazard curves show non-constant hazard rates for any defined age group a piecewise-constant method is inappropriate for this calculation, therefore I will use a fully non-parametric baseline hazard specification using age specific dummy variables to specify the baseline hazard rate. The minimum age of a firm in my sample is 1 while the maximum age is 64. Therefore, I generate 63 age specific dummies to represent all age categories.

Table 3.6 descriptive statistics
This table reports the descriptive statistics of the independent variables used in the study followed by the failed and healthy groups in the second column. The statistics are provided for the whole SME sample, micro, small, and medium.

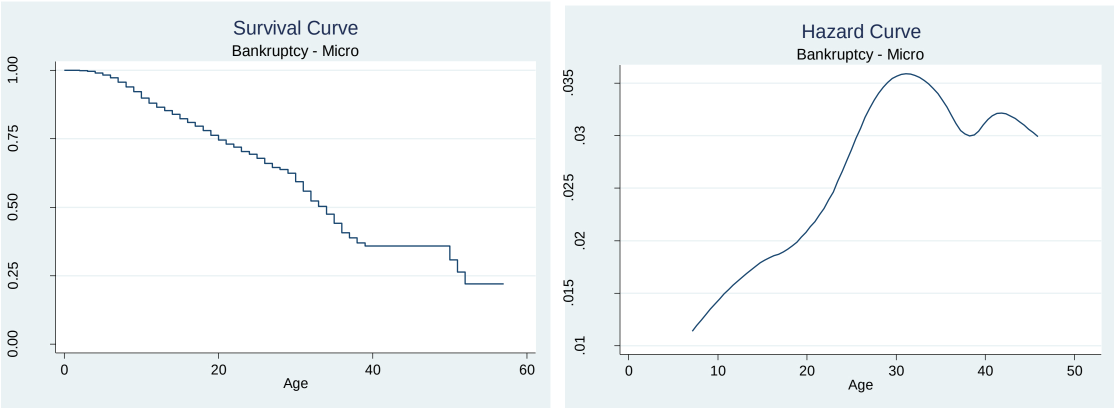
Variable		**Micro**		**Small**		**Medium**		**SMEs**	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
EBIDTAIE									
	Failed	-11.393	21.059	-5.073	13.867	1.601	13.975	-4.518	18.287
	Healthy	-7.216	26.241	-4.178	31.029	10.183	34.941	1.073	33.227
NITA									
	Failed	-0.585	0.498	-0.390	0.449	-0.231	0.345	-0.347	0.457
	Healthy	-0.301	0.519	-0.269	0.406	-0.073	0.255	-0.228	0.412
TLTA									
	Failed	0.760	0.520	0.948	0.413	0.911	0.396	0.840	0.476
	Healthy	0.686	0.522	0.535	0.382	0.484	0.293	0.545	0.390
TCTA									
	Failed	0.153	0.135	0.132	0.115	0.122	0.108	0.130	0.124
	Healthy	0.141	0.129	0.115	0.099	0.101	0.084	0.114	0.101
TTA									
	Failed	0.005	0.021	0.001	0.017	0.006	0.023	0.004	0.021
	Healthy	0.014	0.017	0.008	0.024	0.018	0.030	0.012	0.027
CASALE									
	Failed	0.986	1.021	0.767	0.852	0.496	0.506	0.806	0.896
	Healthy	1.425	1.227	1.150	1.106	0.812	0.823	1.045	1.039
WCTA									
	Failed	-0.006	0.442	-0.007	0.347	0.046	0.340	0.021	0.399
	Healthy	0.047	0.440	0.268	0.358	0.322	0.280	0.245	0.362

Figure 3.1 survival and hazard curves

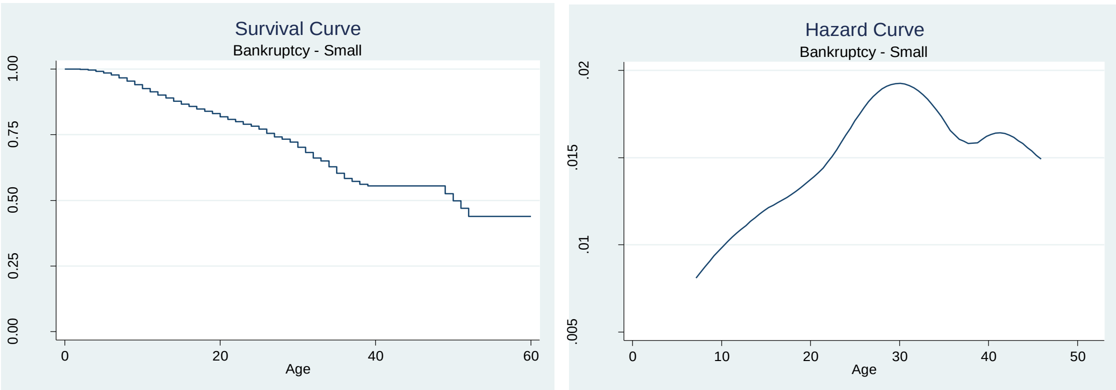
A. SMEs survival and hazard curves



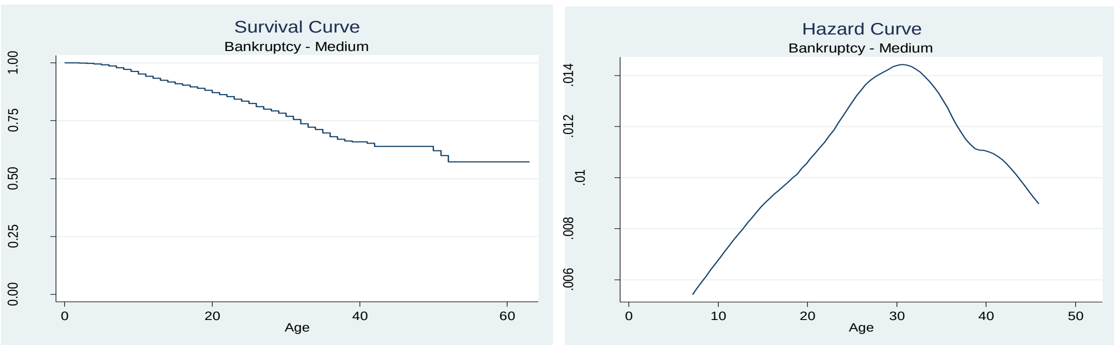
B. Micro SMEs survival and hazard curves



C. Small SMEs survival and hazard curves



D. Medium SMEs survival and hazard curves



3.4.3.2.Discrete-time Duration-dependant Hazard Models

3.4.3.2.1. Hazard Model for all SMEs

The first model developed in this paper is the hazard model for all the SMEs in my sample which contain all the firms having less than 500 employees accounting for a total of 79,016 firm-year observations. In this model I have included all the covariates that are found to be significant during my univariate analysis. Table 3.7 provides the final results of the SMEs prediction model where it can be seen that all the covariates have coefficients of the expected sign. However, the NITA and CASALE covariates fail to provide any significant discriminatory power in the multivariate setup.

3.4.3.2.2. Hazard Model for Micro Firms

This model has been estimated using the Micro SMEs' sample of firms that have less than 20 employees. Table 3.7 reports the final distress prediction model for Micro firms using the six selected covariates. The results in table 3.7 indicate that only two covariates show significant power in identifying the financial distress of micro SMEs namely TLTA and WCTA, whereas EBIDTAIE, NITA, TCTA, TTA, and CASALES exhibit insignificant power in the micro model. These findings are in line with the findings of Gupta et al. (2014) in the UK market that the explanatory power of financial reports increases with the size of the firm. I find that that larger the firm's size the more similar results it provides to the SMEs model for all firms. In addition, after comparison between the small and medium models and the SMEs model, the empirical findings strongly suggest that the credit risk characteristics of micro SMEs differ from other SMEs and need to be considered separately when modelling their credit risks.

3.4.3.2.3. Hazard Model for Small Firms

This model has been estimated using the small SMEs' sample of firms which have has less than 100 and more than 20 employees. The results in table 3.7 indicate that four covariates in the model are insignificant in explaining the financial distress of Small firms namely EBIDTAIE, NITA, WCTA, and CASALES.

3.4.3.2.4. Hazard Model for Medium Firms

This model has been estimated using the medium firms' sample of firms which have less than 500 and more than 100 employees. Medium SMEs enjoy relatively similar results to the SMEs final model showing highly significant covariates (except for NITA and TTA). After a comparison between the results of the two models, I can conclude that there are no strong reasons for creditors and decision makers to treat SMEs and medium firms separately.

Table 3.7 multivariate hazard models
This table reports the estimations corresponding to micro, small, medium, and SMEs respectively. For each segment the table reports the results obtained from respective multivariate hazard analysis followed by goodness of fit measures. ***, **, * indicates the significance at the 1%, 5%, and 10% respectively. The dependant variable is a dummy that equals one if the SME went into bankruptcy and zero otherwise. Both age and industry effects are controlled for in the regressions.

	Micro		**Small**		**Medium**		**SMEs**	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
EBIDTAIE	-0.0025	0.0048	-0.0021	0.0072	-0.0130*	0.0073	-0.0109***	0.0032
NITA	-0.0924	0.2172	-0.0943	0.3574	-0.3329	0.4290	-0.1698	0.1576
TLTA	1.34949***	0.3033	2.8226***	0.4429	2.6630***	0.4647	1.9519***	0.2043
TCTA	0.9417	0.9348	3.1230***	1.3415	2.8267**	1.4312	1.2203**	0.6225
WCTA	-1.186459***	0.0010	-0.6447	0.5101	-3.3204***	0.5819	-0.6221***	0.2444
TTA	-2.0863	4.5838	-15.5357***	7.1535	-11.9163***	5.4457	-7.1121***	2.7305
CASALE	-0.3677	0.1047	-0.2871	0.1842	-0.3697	0.2538	-0.1110	0.0761
Constant	-12.7023***	1.7318	-14.6922***	2.2521	-13.0451***	1.7266	-13.1424***	1.3608
IRC	0.2851***	0.0544	0.3595***	0.0790	0.2243***	0.0671	0.1832***	0.0327
Age dummies	Yes		Yes		Yes		Yes	
Industry control	Yes		Yes		Yes		Yes	
Goodness of fit								
Wald chi2	157.0300***		167.63***		220.9000***		549.9100***	
Log Likelihood	-772.9203		-806.1630		-1124.5943		-2933.9049	
AIC	5991.81		2367.189		1720.326		1641.84	
BIC	6567.009		2822.551		2179.792		2029.234	
Number of observations	16,614		23,640		36,630		79,016	

3.4.4. Model Forecasting Accuracy

As mentioned in section (3.3.2.) to test the effectiveness of the models developed in the perdition of SMEs bankruptcy and their forecasting abilities table 3.8 provides the classification performance measure for each of the prediction models developed.

The results reported in all of these deciles indicate the percentage of failed SMEs that were classified as failed for the out-of-sample period after re-running all the models.

Furthermore, the reported numbers in the first decile for each model indicate the ability of each model to correctly distinguish the failed from non-failed SMEs. First, the bankruptcy probabilities for each firm were calculated for each model and then these probabilities were compared with the incidence of the actual event for each firm in the subsequent year. Afterwards, I have classified the firms that were correctly predicted (e.g. the model was able to correctly predict the actual default in the subsequent year (t+1) by providing the highest bankruptcy probability in year t) into deciles. For example, in table 3.8 the full SMEs model in the first decile shows that 24.41% of the SMEs were correctly predicted with very high accuracy. The second decile indicates that 31% of SMEs were correctly predicted but with a lower accuracy than the first decile and so on. The last five deciles 6 to 10 indicate the percentage of SMEs that were not accurately predicted by the model. Similarly these interpretations can be applied to the different size model namely micro, small, and medium.

Therefore, it can be concluded that in terms of the models classification performance I find that all of the four models are able to capture more than 60% of the distress firms in the top three deciles which is considered to be a good percentage whereas the total number of the last five percentiles is less than 20%.

Table 3.8 classification performance measure
This table reports the classification performance measures for each of the SMEs' size segments: micro, small, medium, and whole SMEs sample over the ten classification deciles for the period from 2009 till 2013.

Decile	Micro	Small	Medium	SMEs
1	18.67%	23.67%	21.45%	24.41%
2	25.51%	24.00%	27.65%	31.00%
3	19.00%	17.33%	15.75%	13.73%
4	9.51%	14.55%	12.45%	8.33%
5	8.66%	8.32%	9.05%	5.00%
6 , 10	18.65%	12.13%	13.65%	17.53%
Total	100.00%	100.00%	100.00%	100.00%

Table 3.9 definition of variables

Code	Definition	Compustat item code
Profitability		
EBIDTAIE	Earnings before interest taxes depreciation and amortization/Interest expense	EBIDTA/XINT
EBIDTATA	Earnings before interest taxes depreciation and amortization/Total Assets	EBIDTA/AT
NISALE	Net income to net sales	NI/SALE
RETA	Retained earnings to Total assets	RE/AT
NITA	Net income to Total Assets	NI/AT
NITE	Net income to total equity	NI/TE
Leverage		
XINTTA	Financial Expenses/Total Assets	XINT/AT
CLTA	Total current liabilities/Total assets	LCT/AT
TCTA	Trade Creditors/Total Assets	AP/AT
TLTA	Total Non-Equity to Total Assets	AT/AT
STDEBV	short term debt to equity book value	DLC/SEQ
TDTA	Total debt to total assets	DT/AT
Activity		
CETL	Capital employed/Total liabilities	(AT - LCT)/LT
TTA	Taxes/Total Assets	TXT/AT
CG	Capital Growth; Capital/Capital[_n-1]	((AT-LCT)/(AT[_n-1]-LCT[_n-1]))-1
WCSALE	Working capital to Sales	WCAP/SALE
CASALE	current asset to Sales	ACT/SALE
CSIS	cash and short-term investments/Sales	CHE/SALE
Liquidity		
WCTA	Working capital/Total Assets	WCAP/AT
CSIAT	Cash and short term investment to Total Assets	CHE/AT
Solvency		
CACL	current assets to current liabilities	ACT/LCT
QCACL	(current assets - inventory) to current liabilities	(ACT-INVT)/LCT

3.5. Conclusion

This chapter investigates the extent to which the size of SMEs affects their probabilities of bankruptcy. To answer this question I classify SMEs into three size categories (micro, small, and medium) while modelling for bankruptcy prediction. I will try to capture any differences that exist among these categories and to what extent this might help lenders to improve their credit models.

I apply discrete-time duration-dependent hazard rate modelling techniques to develop separate bankruptcy prediction models for micro, small, and medium firms respectively, using a relatively large database of US firms. I compare their performance with the model developed for SMEs, as a whole including micro, small, and medium firms.

My empirical analysis is performed using panel data available to us from the Compustat database. The sample employs annual firm-level accounting data for 465 bankrupt and 11,117 non-bankrupt US small and medium-sized enterprises having less than 500 employees and average annual receipts of less than $ 7.5 million, covering an analysis period from 1980 to 2013.

In order to test the effectiveness of the models developed in the prediction of SMEs bankruptcy and their forecasting abilities I perform a bankruptcy out-of-sample prediction test similar to Shumway (2001). I specify my out-of-sample period to be from 2009 to 2013. Therefore, I re-calculate all the forecasting models for the period from 1980 to 2008 and then year by year I rank the firms into deciles based on their computed bankruptcy probabilities. The firms most likely to default in the subsequent year are placed into the first decile, the next most likely to default in the second decile, and so on. Hence, the higher percentage of firms that experience default in the top deciles reflects a model with better classification performance. All the multivariate models developed exhibit strong classification performance capturing more than 60% of the distressed firms in the top three deciles which is considered to be a good percentage whereas the total number in the last five deciles is less than 20%.

A comparison of the default prediction models for medium SMEs and the whole SME sample suggest that an almost identical set of explanatory variables affect the default probabilities leading us to believe that there is no material impact on the decision making process of treating each of these groups separately. However, comparisons between the micro and small SMEs and the whole of the SME firms strongly suggest that they need to be considered separately when modelling credit risk for them. Based on my findings, I advise lenders to provide a separate credit modelling assessment for micro and small SMEs since financial reports do not provide sufficient information about the likelihood of their default.

Chapter Four

4. Solving the SMEs' Extreme Debt Conservatism Puzzle

4.1. Introduction

Capital structure theory has attracted a lot of attention from scholars around the world since the seminal work of Modigliani and Miller in 1958. Most of these studies try to find out the reasons behind the choice of debt and equity financing and what is the optimal level of debt-equity that should be held in the firm. However, few studies try to tackle the phenomenon of extreme debt conservatism in some companies, which have zero outstanding debt, including both short – and long-term debt, in their capital structure. In recent years over 20% of US firms such as Microsoft, Cisco Systems, and Walgreen have changed their capital structure toward debt-free levels [12].

Small and medium-sized enterprises (SMEs) face higher barriers to external financing than larger firms (Ardic et al., 2011), which poses more constraints on them obtaining commercial bank financing, especially long-term loans. This might be due to lack of collateral, small cash flows, inadequate credit history, and high risk premiums (IFC, 2010). A growing body of literature focuses on the determinants of SMEs' capital structure in the US (Berger and Udell, 1998), Europe (Sogorb-Mira, 2005; Ramalho and da Silva, 2009), and Asia (Matlay et al., 2006). However, to my knowledge there has been no study yet that has tried to explore the zero-debt[13] puzzle of SMEs. Therefore, this study contributes to the existing literature on SMEs' capital structure by attempting to provide potential explanations for the reasons behind the choice of zero-debt along various dimensions and examining a number of economic mechanisms that are believed to further explain the phenomenon of extreme debt conservatism in SMEs. Furthermore,

[12] "Companies with no debt fly high" by Matt Krantz, USA Today on August 21, 2002.
[13] Zero-debt and debt-free have the same meaning and they are used interchangeably in this chapter.

I study to what extent different SME size segments (namely micro, small, and medium) affect the debt-free decision.

The extreme debt puzzle refers to the idea that certain firms prefer to have no leverage compared to that which would maximize the firm value from a static trade-off theory point of view (Miller, 1977; Graham, 2000). A study by Korteweg (2010) encourages zero-debt firms to reach their optimal leverage ratio so they can increase firm value by approximately 5.5%. Recently, studies on dynamic trade-off theory find relatively lower optimal leverage ratios (Goldstein et al., 2001; Strebulaev, 2007). However, they are still unable to provide explanations for the zero-debt usage in some firms.

Studying the zero-debt puzzle in SMEs will help in the understanding of their capital structure decisions. The zero-debt phenomenon may be considered to be a special case of the low-leverage puzzle which refers to the fact that some firms tend to keep low leverage ratios in their capital structure relative to those indicated by the normally expected models of capital structure. However, examining zero-debt firms enjoys certain advantages over low-leverage studies. According to Parson and Titman (2009) the measurement of leverage ratio suffers from considerable ambiguity. For example there exists a difference when scaling debt by market value or book value (Strebulaev and Yang, 2013). In this study I will see whether such a difference between market and book value of debt exists in low leverage SMEs (usually SMEs having leverage ratios between 0 and 5% in line with Minton and Wruck (2002) and Strebulaev and Yang (2013)). In addition, spurious correlation is induced when dividing dependant and independent variables by common or correlated variables as in typical cross-sectional leverage regressions (Powell et al., 2009).

Moreover, a few scholars such as Ang (1991) have argued that the different capital structure theories introduced in the literature were developed without taking into consideration small and medium enterprises. However, the majority of scholars such as

Michaelas et al. (1999) and Lucey and Mac an Bhaird (2006) praise these theories for allowing the formulation of testable hypotheses on the financing decisions of SMEs. Furthermore, Cassar and Holmes (2003) support the latter argument stating that the corporate finance theory provides the theoretical underpinnings necessary for any research on the capital structure of SMEs with one major exception. This exception lies in theories which involve conflicts between owners and management since SMEs tend to have a less pronounced separation of ownership and management than larger firms. Therefore, in this chapter it should be highlighted that all the theories designed for large listed companies can be applied to SMEs as well.

I find that on average 20% of firm-year observations over the whole sample period from 1980 to 2014 exhibit zero-debt behaviour, and this percentage decreases across each size segment from micro, through small, to medium, providing initial evidence that the larger the firm, the easier its access to debt. Moreover, it is found that the debt-free phenomenon is relatively persistent, since for more than 95% of SMEs in my sample, the maximum number of debt-free years is seven years.

In addition, I test empirically the theoretical situations that might affect the capital structure decisions within the SME, such as borrowing constraints, which are the potential constraints on the firm's access to debt, SMEs' valuation and financing activities, investment opportunities and profitability, and dividend payments. My findings suggest that borrowing constraints and financing activities play a significant role in the debt-free capital structure decisions of the SME. A surprising result is that a large number of debt-free SMEs pay significantly higher dividends than their counterparts with debt. Finally, I find that non-debt tax shields, pension obligations, and lease commitments do not play a significant role in explaining the debt-free policy.

Finally, it can be generalised from my findings that SMEs are more inclined to use trade-off theory rather than the pecking order theory while deciding on their capital structure composition. For example, my results show that debt-free SMEs pay significantly higher dividends than SMEs with debt across the different size segments. This indicates that debt-free SMEs try to satisfy shareholders so that they can raise external equity on favourable terms, thus effectively replacing payouts to debt-holders with payouts to equity holders and without the adverse effects of the agency problem of debt which contradicts the pecking order theory. In addition, under the pecking order theory, it is believed that profitable SMEs tend to borrow less cash since they are able to generate sufficient cash flow to cover their financing. However, I find that free cash flows and operating cash flows are significantly lower for debt-free SMEs for the whole sample compared to the SMEs with debt.

The rest of the chapter is organized as follows. Section 4.2 describes the data and provides summary statistics. Section 4.3 discusses the empirical implications of borrowing constraints, valuation and financing activities, investment opportunities and profitability, and dividend payments. Section 4.4 provides detailed univariate analysis for a certain number of variables to test empirically the theoretical implications discussed in the previous section. Section 4.5 presents an alternative empirical analysis as to why SMEs become debt-free. Section 4.6 provides results for correlation and regression analysis. Section 4.7 provides a summary and concluding remarks.

4.2. Data

In this chapter I employ data extracted from the Compustat database for the period from 1980 until 2014. My data consists of all available annual information for US SMEs. Small and medium-sized enterprises are defined according to the Small Business Administration (SBA) as having fewer than 500 employees and average annual receipts of less than $7.5 million[14]. I then divide my sample according to firms' size into micro, small, and medium enterprises, where the "Micro" firms have fewer than 10 employees;

[14] For more detailed definition see, El Kalak and Hudson (2015a)

firms are classified as "Small" if they have more than or equal to 10 but fewer than 50 employees; and "Medium" firms if they have more than or equal to 50 and fewer than 500 employees.

Furthermore, in line with other studies, I exclude financial, insurance, and utility SMEs from my sample. These eliminated SMEs have industrial classification (SIC) codes from 6000 to 6999 for financial SMEs and 4900 to 4949 for regulated utilities. In addition, I remove all non- US firms with International Standards Organization country code of incorporation (FIC) not equal to USA. SMEs are required to have positive values of common equity, total assets, stock price at the end of the fiscal year, and number of shares outstanding. There are 95,450 firm-year observations that satisfy these criteria of which 32,244 are micro SMEs, 26,230 are small SMEs, and 36,669 are medium SMEs. These observations include 18,764 debt-free observations for the whole SMEs sample, 8,135 for micro SMEs, 5,028 for small SMEs, and 5,577 for medium SMEs. The time in my research is indicated by (t) which refers to the calendar date of the fiscal year-end. Each SME firm is defined as a debt-free SME if it has neither current nor long –term debt in a given year and an SME firm with any amount of debt in a given year is classed as a debt SME.

Table 4.1 reports the frequency of debt-free observations of SMEs relative to the total number of observations in the sample in each year between 1980 and 2014. In addition, this table reports the frequency of debt-free observations relative to each size segment, namely, micro, small, and medium. Column 4 shows the fraction of debt-free SMEs relative to the total observations in the sample in each year between 1980 and 2014. On average, 20% of firm-year observations over the whole sample period exhibit zero debt behaviour ranging from a minimum of 11.01% in 1980 to a maximum of 32.65% in 2014. The percentage of debt-free observations enjoys a steady increase throughout the sample period, which indicates a growing preference among SMEs to eschew debt and gradually become debt-free. This result can also be found in each size segment, albeit with slight variations in the fractions of debt-free percentages across years, where the minimum of debt-free observations for micro SMEs can be found in 1983 with 18.78%, whereas it is found in 1985 for small SMEs with 11.05%, and the minimum percentage of debt-free observations for medium SMEs was reported in 1981. Furthermore, it is noticed that on average the percentage of firm-year observations decreases across each size segment, with 25% for micro SMEs, 19% for small SMEs, and 15% for medium SMEs. These findings provide supportive evidence for the argument that the larger the firm, the easier its access to debt, hence its opportunity to use debt increases.

Table 4.1 frequency of debt-free observations

Debt-free represents the observations where the SME has a zero book debt in a given year. Percentage reports the ratio of debt-free observations to the total number of observations in each year.

SMEs					Micro				
Year	Debt	Debt-Free	Percentage	Total Observation	Year	Debt	Debt-Free	Percentage	Total Observation
1980	1,891	234	11.01	2,125	1980	471	115	19.62	586
1981	1,973	263	11.76	2,236	1981	483	130	21.21	613
1982	2,178	299	12.07	2,477	1982	620	158	20.31	778
1983	2,335	324	12.19	2,659	1983	653	151	18.78	804
1984	2,387	341	12.50	2,728	1984	646	158	19.65	804
1985	2,567	359	12.27	2,926	1985	796	185	18.86	981
1986	2,726	408	13.02	3,134	1986	864	202	18.95	1,066
1987	2,626	432	14.13	3,058	1987	783	215	21.54	998
1988	2,511	440	14.91	2,951	1988	684	233	25.41	917
1989	2,454	409	14.29	2,863	1989	693	206	22.91	899
1990	2,452	425	14.77	2,877	1990	768	218	22.11	986
1991	2,523	455	15.28	2,978	1991	769	217	22.01	986
1992	2,570	518	16.77	3,088	1992	771	227	22.75	998
1993	2,637	550	17.26	3,187	1993	722	208	22.37	930
1994	2,697	597	18.12	3,294	1994	724	213	22.73	937
1995	3,123	692	18.14	3,815	1995	1,018	287	21.99	1,305
1996	3,035	733	19.45	3,768	1996	867	257	22.86	1,124
1997	2,822	707	20.03	3,529	1997	654	238	26.68	892
1998	2,969	771	20.61	3,740	1998	912	316	25.73	1,228
1999	2,923	756	20.55	3,679	1999	806	302	27.26	1,108
2000	2,660	770	22.45	3,430	2000	729	322	30.64	1,051
2001	2,544	745	22.65	3,289	2001	763	316	29.29	1,079
2002	2,368	739	23.79	3,107	2002	798	323	28.81	1,121
2003	2,130	711	25.03	2,841	2003	772	285	26.96	1,057
2004	1,909	708	27.05	2,617	2004	707	276	28.08	983
2005	1,780	686	27.82	2,466	2005	638	268	29.58	906
2006	1,673	639	27.64	2,312	2006	595	253	29.83	848
2007	1,566	615	28.20	2,181	2007	546	245	30.97	791
2008	1,486	577	27.97	2,063	2008	583	250	30.01	833
2009	1,447	551	27.58	1,998	2009	604	234	27.92	838
2010	1,344	551	29.08	1,895	2010	576	249	30.18	825
2011	1,314	562	29.96	1,876	2011	605	283	31.87	888
2012	1,481	553	27.19	2,034	2012	744	290	28.05	1,034
2013	1,356	533	28.22	1,889	2013	631	252	28.54	883
2014	229	111	32.65	340	2014	114	53	31.74	167
Total	76,686	18,764	20	95,450	Total	24,109	8,135	25	32,244

Table 4.1 frequency of debt-free observations (continued)

Debt-free represents the observations where the SME has a zero book debt in a given year. Percentage reports the ratio of debt-free observations to the total number of observations in each year.

Small					Medium				
year	Debt	Debt-Free	Percentage	Total Observation	year	Debt	Debt-Free	Percentage	Total Observation
1980	450	56	11.07	506	1980	952	63	6.21	1,015
1981	496	69	12.21	565	1981	981	62	5.94	1,043
1982	531	71	11.79	602	1982	1,011	70	6.48	1,081
1983	624	83	11.74	707	1983	1,046	87	7.68	1,133
1984	662	85	11.38	747	1984	1,064	97	8.35	1,161
1985	684	85	11.05	769	1985	1,072	87	7.51	1,159
1986	740	104	12.32	844	1986	1,105	102	8.45	1,207
1987	725	106	12.76	831	1987	1,109	111	9.10	1,220
1988	752	108	12.56	860	1988	1,056	98	8.49	1,154
1989	758	104	12.06	862	1989	990	99	9.09	1,089
1990	705	102	12.64	807	1990	968	105	9.79	1,073
1991	729	112	13.32	841	1991	1,019	126	11.00	1,145
1992	746	128	14.65	874	1992	1,045	162	13.42	1,207
1993	765	173	18.44	938	1993	1,145	168	12.80	1,313
1994	792	197	19.92	989	1994	1,174	186	13.68	1,360
1995	846	191	18.42	1,037	1995	1,250	213	14.56	1,463
1996	882	221	20.04	1,103	1996	1,275	253	16.56	1,528
1997	860	204	19.17	1,064	1997	1,303	265	16.90	1,568
1998	779	210	21.23	989	1998	1,269	245	16.18	1,514
1999	837	204	19.60	1,041	1999	1,273	250	16.41	1,523
2000	759	198	20.69	957	2000	1,164	249	17.62	1,413
2001	737	183	19.89	920	2001	1,036	246	19.19	1,282
2002	648	171	20.88	819	2002	916	245	21.10	1,161
2003	596	195	24.65	791	2003	759	228	23.10	987
2004	505	193	27.65	698	2004	694	239	25.62	933
2005	496	179	26.52	675	2005	643	238	27.01	881
2006	458	170	27.07	628	2006	615	216	25.99	831
2007	435	189	30.29	624	2007	580	181	23.78	761
2008	385	166	30.13	551	2008	515	161	23.82	676
2009	352	155	30.57	507	2009	489	162	24.88	651
2010	354	156	30.59	510	2010	412	146	26.16	558
2011	341	139	28.96	480	2011	366	139	27.52	505
2012	356	136	27.64	492	2012	378	126	25.00	504
2013	357	157	30.54	514	2013	365	123	25.20	488
2014	60	28	31.82	88	2014	53	29	35.37	82
Total	21,202	5,028	19	26,230	Total	31,092	5,577	15	36,669

Table 4.2 presents the distribution of SMEs across the number of debt-free years during the sample period. I further report the number of SMEs with debt-free years for each size segment of the SMEs sample. From the SMEs columns, during my sample period around 37% of the SMEs had at least one year of debt-free capital structure. Furthermore, it is observed that only a few SMEs were debt-free for most of the sample period. In addition, approximately 95% of SMEs in my sample have less than seven debt-free years.

A general overview on the size segments of SMEs distribution across the debt-free years provides further support to the argument that the larger the firm, the easier its access to debt, and hence the greater its opportunity to use debt. The percentage of being debt-free for zero years[15] increases when moving from micro to medium SMEs. It is reported that 59.61% of micro SMEs have zero years debt-free, this percentage increases to 63.72% for small SMEs, and 73.47% for medium SMEs. The cumulative percentage columns report that for 95% of my micro, small, and medium SMEs, the numbers of debt-free years are less than 7 years, 8 years, and 5 years respectively.

It could be argued that the debt-free puzzle is partly driven by industry specific factors. Therefore, the distribution of debt and debt-free SMEs across industry classification for each size segment is shown in table 4.3 The industry classification is performed based on the three-digit SIC code provided by Compustat. There is indeed a considerable amount of variation in the extent of debt-free behaviour across industries for each SME size segment. The highest numbers of total observations and number of debt-free observations are reported for manufacturing SMEs with 48,502 firm-year observations and 9,707 debt-free observations. However, the public administration sector has the highest percentage of debt-free observations, with around 33%. These findings are similar to micro SMEs with around 45% of debt-free observations belong to public

[15] The zero year debt-free percentage indicates that SMEs have never been debt-free during their lives.

administration SMEs. However, for small SMEs the manufacturing sector yielded the highest percentage of debt-free observations with slightly over 22% whereas construction industries have less than 5% of debt-free observations. Regarding the medium SMEs, manufacturing and service industries constitute by far the biggest portion of debt-free and total number of observations, while service industries have the highest percentage of debt-free observations with around 22%.

Table.4.2 the distribution of SMEs across the number of debt-free years
No. of debt free years represents the number of years during which the firm has no debt. No. of SMEs represents the number of SMEs within each group. (%) represents the percentage of SMEs in each debt-free year to the total number of SMEs in the group. Cum % represents the cumulative percentage of the number of SMEs. The data consists of 95,450 firm-year observation distributed over 14,093 SMEs for the period from 1980 till 2014.

SMEs				Micro			
No. of DF years	No. of SMEs	%	Cum. %	No. of DF years	No. of SMEs	%	Cum. %
0	8,922	63.31	63.31	0	5,202	59.61	59.61
1	1,728	12.26	75.57	1	1,193	13.67	73.29
2	1,066	7.56	83.13	2	744	8.53	81.81
3	663	4.7	87.84	3	449	5.15	86.96
4	423	3	90.84	4	282	3.23	90.19
5	287	2.04	92.88	5	182	2.09	92.28
6	238	1.69	94.56	6	169	1.94	94.21
7	156	1.11	95.67	7	108	1.24	95.45
8	137	0.97	96.64	8	95	1.09	96.54
9	95	0.67	97.32	9	60	0.69	97.23
10	82	0.58	97.9	10	53	0.61	97.83
11	53	0.38	98.28	11	35	0.4	98.24
12	37	0.26	98.54	12	28	0.32	98.56
13	41	0.29	98.83	13	28	0.32	98.88
14	38	0.27	99.1	14	21	0.24	99.12
15	17	0.12	99.22	15	13	0.15	99.27
16	25	0.18	99.4	16	15	0.17	99.44
17	21	0.15	99.55	17	17	0.19	99.63
18	12	0.09	99.63	18	9	0.1	99.74
19	6	0.04	99.67	19	1	0.01	99.75
20	5	0.04	99.71	20	2	0.02	99.77
21	8	0.06	99.77	21	3	0.03	99.81
22	12	0.09	99.85	22	8	0.09	99.9
23	4	0.03	99.88	23	2	0.02	99.92
24	9	0.06	99.94	24	4	0.05	99.97
25	3	0.02	99.96	25	1	0.01	99.98
26	1	0.01	99.97	26	0	0	99.98
27	1	0.01	99.98	27	1	0.01	99.99
28	0	0	99.98	28	0	0	99.99
29	1	0.01	99.99	29	1	0.01	100
30	0	0	99.99	30	0	0	100
31	0	0	99.99	31	0	0	100
32	1	0.01	99.99	32	0	0	100
33	0	0	99.99	33	0	0	100
34	1	0.01	100	34	0	0	100
Total	14,093	100		Total	8,726	100	

Table.4.2 the distribution of SMEs across the number of debt-free years (continued)
No. of debt free years represents the number of years during which the firm has no debt. No. of SMEs represents the number of SMEs within each group. (%) represents the percentage of SMEs in each debt-free year to the total number of SMEs in the group. Cum % represents the cumulative percentage of the number of SMEs. The data consists of 95,450 firm-year observation distributed over 14,093 SMEs for the period from 1980 till 2014.

Small				Medium			
No. of DF years	No. of SMEs	%	Cum. %	No. of DF years	No. of SMEs	%	Cum. %
0	1,458	63.72	63.72	0	2,262	73.47	73.47
1	258	11.28	75	1	277	9	82.46
2	156	6.82	81.82	2	166	5.39	87.85
3	108	4.72	86.54	3	106	3.44	91.3
4	73	3.19	89.73	4	68	2.21	93.5
5	54	2.36	92.09	5	51	1.66	95.16
6	37	1.62	93.71	6	32	1.04	96.2
7	28	1.22	94.93	7	20	0.65	96.85
8	20	0.87	95.8	8	22	0.71	97.56
9	15	0.66	96.46	9	20	0.65	98.21
10	17	0.74	97.2	10	12	0.39	98.6
11	5	0.22	97.42	11	13	0.42	99.03
12	7	0.31	97.73	12	2	0.06	99.09
13	9	0.39	98.12	13	4	0.13	99.22
14	9	0.39	98.51	14	8	0.26	99.48
15	2	0.09	98.6	15	2	0.06	99.55
16	8	0.35	98.95	16	2	0.06	99.61
17	4	0.17	99.13	17	0	0	99.61
18	2	0.09	99.21	18	1	0.03	99.64
19	2	0.09	99.3	19	3	0.1	99.74
20	2	0.09	99.39	20	1	0.03	99.77
21	3	0.13	99.52	21	2	0.06	99.84
22	2	0.09	99.61	22	2	0.06	99.9
23	1	0.04	99.65	23	1	0.03	99.94
24	4	0.17	99.83	24	1	0.03	99.97
25	2	0.09	99.91	25	0	0	99.97
26	1	0.04	99.96	26	0	0	99.97
27	0	0	99.96	27	0	0	99.97
28	0	0	99.96	28	0	0	99.97
29	0	0	99.96	29	0	0	99.97
30	0	0	99.96	30	0	0	99.97
31	0	0	99.96	31	0	0	99.97
32	0	0	99.96	32	1	0.03	100
33	0	0	99.96	33	0	0	100
34	1	0.04	100	34	0	0	100
Total	2,288	100		Total	3,079	100	

Table 4.3 industry code construction for SMEs
The above table gives the SIC codes unique industry code along with the name of each industry. % of debt-free observations reports the ratio of debt-free observations in each industry divided by the total number of observations in the same industry. The last column gives the total number of observations during the sample period 1980 - 2014 in each of these industries.

IND Code	SIC code	Industry name	# of Debt-Observation	# of Debt-Free Observations	% of Debt-Free Observations	Total # of Observations
1	<1000	Agriculture, Forestry and Fisheries	462	102	18.09	564
2	1000 to less than 1500	Mineral Industries	6856	1777	20.58	8633
3	1500 to less than 1800	Construction Industries	1150	109	8.66	1259
4	2000 to less than 4000	Manufacturing	38795	9707	20.01	48502
5	4000 to less than 4899	Transportation and Communications	1970	286	12.68	2256
6	4950 to less than 5200	Wholesale Trade	4186	606	12.65	4792
7	5200 to less than 6000	Retail Trade	3206	348	9.79	3554
8	7000 to less than 8900	Service Industries	17922	4786	21.08	22708
9	9100 to less than 10000	Public Administration	2139	1043	32.78	3182
		Total # of Observations	76686	18764	19.66	95450

Table 4.3 industry code construction for micro SMEs (continued)
The above table gives the SIC codes unique industry code along with the name of each industry. % of debt-free observations reports the ratio of debt-free observations in each industry divided by the total number of observations in the same industry. The last column gives the total number of observations during the sample period 1980 - 2014 in each of these industries.

IND Code	SIC code	Industry name	# of Debt-Observation	# of Debt-Free Observations	% of Debt-Free Observations	Total # of Observations
1	<1000	Agriculture, Forestry and Fisheries	140	60	30	200
2	1000 to less than 1500	Mineral Industries	3960	1464	26.99	5424
3	1500 to less than 1800	Construction Industries	343	60	14.89	403
4	2000 to less than 4000	Manufacturing	9729	3347	25.60	13076
5	4000 to less than 4899	Transportation and Communications	680	179	20.84	859
6	4950 to less than 5200	Wholesale Trade	1093	300	21.54	1393
7	5200 to less than 6000	Retail Trade	1126	151	11.82	1277
8	7000 to less than 8900	Service Industries	5937	1660	21.85	7597
9	9100 to less than 10000	Public Administration	1101	914	45.36	2015
		Total # of Observations	24109	8135	25.23	32244

Table 4.3 industry code construction for small SMEs (continued)
The above table gives the SIC codes unique industry code along with the name of each industry. % of debt-free observations reports the ratio of debt-free observations in each industry divided by the total number of observations in the same industry. The last column gives the total number of observations during the sample period 1980 - 2014 in each of these industries.

IND Code	SIC code	Industry name	# of Debt-Observation	# of Debt-Free Observations	% of Debt-Free Observations	Total # of Observations
1	<1000	Agriculture, Forestry and Fisheries	174	27	13.43	201
2	1000 to less than 1500	Mineral Industries	1703	246	12.62	1949
3	1500 to less than 1800	Construction Industries	286	14	4.67	300
4	2000 to less than 4000	Manufacturing	11499	3261	22.09	14760
5	4000 to less than 4899	Transportation and Communications	496	41	7.64	537
6	4950 to less than 5200	Wholesale Trade	1109	184	14.23	1293
7	5200 to less than 6000	Retail Trade	540	59	9.85	599
8	7000 to less than 8900	Service Industries	4811	1112	18.77	5923
9	9100 to less than 10000	Public Administration	584	84	12.57	668
		Total # of Observations	**21202**	**5028**	**19.17**	**26230**

Table 4.3 industry code construction for medium SMEs (continued)
The above table gives the SIC codes unique industry code along with the name of each industry. % of debt-free observations reports the ratio of debt-free observations in each industry divided by the total number of observations in the same industry. The last column gives the total number of observations during the sample period 1980 - 2014 in each of these industries.

IND Code	SIC code	Industry name	# of Debt-Observation	# of Debt-Free Observations	% of Debt-Free Observations	Total # of Observations
1	<1000	Agriculture, Forestry and Fisheries	143	15	9.49	158
2	1000 to less than 1500	Mineral Industries	1190	67	5.33	1257
3	1500 to less than 1800	Construction Industries	515	34	6.19	549
4	2000 to less than 4000	Manufacturing	17409	3086	15.06	20495
5	4000 to less than 4899	Transportation and Communications	789	66	7.72	855
6	4950 to less than 5200	Wholesale Trade	1968	122	5.84	2090
7	5200 to less than 6000	Retail Trade	1511	136	8.26	1647
8	7000 to less than 8900	Service Industries	7120	2007	21.99	9127
9	9100 to less than 10000	Public Administration	447	44	8.96	491
		Total # of Observations	**31092**	**5577**	**15.21**	**36669**

4.3. Theoretical Discussions

As shown in the previous section, more than 19% of the SMEs overall sample is debt-free, and the number of debt-free SMEs is growing in recent years. These findings suggest that the debt-free puzzle in the SMEs world is economically important. Therefore, this section provides theoretical discussions about the existing theories of capital structure in general and the debt-free puzzle in particular. Moreover, I link these theories with previous empirical findings in order to set some ground rules for the empirical analysis that follows in the next section.

4.3.1. Borrowing Constraints

It is important when studying the firm's leverage decisions not to focus only on the determinants of its optimal leverage (the demand side) but also to focus on the supply side of the equation, which is the potential constraint on the firm's access to debt. The literature emphasizes the significance of firm's size and age in its decision about capital structure. For example a study by Bolton and Freixas (2000) finds that start up and small firms prefer to take loans or issue bonds to finance their investments in order to reduce their information dilution costs; however, due to their risky nature accessing debt via loans or bonds is usually associated with high costs. Faulkender and Petersen (2006) state that firms with access to the public debt market issue more debt compared to firms without such access. In line with these findings Diamond (1991) argues that firms in their early life are most likely to have loan applications rejected since they do not enjoy favourable track records of borrowing. Finally, Barclay and Morellec (2006) support the previous findings and show that firms in their reputation acquisition stage will tend not to use debt because of its high cost and low benefits. In line with the literature, I can summarize that firm's age and size pose borrowing constraints on firms which may turn them into debt-free firms.

4.3.2. SMEs Valuation and Financing Activities

The literature shows that market timing for selling (buying or repurchasing) overvalued (undervalued) shares plays a significant role in determining the firm's capital structure in the short run (Baker et al., 2003). Graham and Harvey (2001) find that two-thirds of CFOs agree that the amount by which their stock is undervalued or overvalued is an important or very important consideration for equity issuance. In addition, Jenter (2005) and Jenter et al. (2011) provide empirical evidence that managers attempt to time the market in their corporate financing activities.

In line with these points, Welch (2004) argues that debt levels in firms change according to the price of shares in the market. He finds that higher level of debt ratios are found in firms with under-performing shares, while lower levels of debt are found in firms with over-performing shares. Alti (2006), Flannery and Rangan (2006), Kayhan and Titman (2007), and Huang and Ritter (2009) also suggest that within the pecking order theory of capital structure, firms adjust leverage in the opposite direction to their equity financing. This is also consistent with the trade-off model with transaction costs between the tax advantage and default of debt on the one hand with the benefits of issuing or repurchasing equity by investors on the other hand (Huang and Ritter, 2009). The optimal leverage is achieved when the marginal benefit of debt financing equals that of equity financing. The more optimistic investors are relative to the manager, the higher the marginal benefit of equity issuance and the lower the optimal leverage (Yang, 2013). Therefore, it can be concluded that firms tend to take advantage of high stock valuation and shift to a debt-free capital structure by issuing equity as a mean of financing.

4.3.3. Investment Opportunities and Profitability

In contrast to the trade-off theory, in the pecking order theory there is no optimal capital structure. Myers and Majluf (1984) argue that the capital structure decision is driven by the firm’s desire to finance new investments internally then with low-risk debt and finally with equity. Furthermore, according to the dynamic capital structure model, Fama and French (2002) and Goldstein et al. (2001) emphasize the importance of determining future financing needs as well as current financing costs in the optimal capital structure. Therefore, given the adjustment costs of capital structure or adverse selection costs, firms with greater expected investments tend to become debt-free in order to avoid missing future investments. In addition, the pecking order theory states a negative relationship between the firm’s profitability and leverage ratio. This argument shows that more profitable firms are able to generate sufficient cash flow to cover their financing needs and so take on less debt (Myers, 1984).

Both the pecking order theory and trade-off theory assume a perfectly aligned relationship between managers and the firm’s stockholders. Jensen and Meckling (1976) and Jensen (1986) argue that in reality two types of conflicts arise between managers and shareholders, and between shareholders and debt-holders. Since I study SMEs, it is argued that managers are also often the shareholders; hence, no serious conflict arises here. However, a serious agency problem arises within the SMEs between shareholders and debt-holders.Easterbrook (1984) and Jensen (1986) recommend the use of debt payments or dividend payments to restrict managerial discretion by controlling free cash flows in the hands of managers. Furthermore, DeAngelo and DeAngelo (2007) find that more profitable firms prefer dividend payments rather than debt payments in addressing the agency problem. Hence, I can hypothesise that larger firms with higher profits relative to investment opportunities tend to become debt free by paying more dividends to mitigate the agency problem.

4.3.4. Dividend Payments

Signalling theory is one of the dividend theories that justify paying dividends to build the firm’s reputation, which helps in attracting shareholders’ wealth (La Porta et al., 2000). Therefore, if the firm is in need of external financing, it should attract more investors through paying dividends. Gomes (2000) argues that high-growth firms have stronger incentives to establish a good reputation to support future external financing. Hence, it is not surprising to see that high growth firms have a higher tendency to become debt-free firms, since their reputation established by high dividend payments allows them to raise external equity on favourable terms. Thus they effectively replace payouts to debt-holders with payouts to equity-holders. Furthermore, some studies such as Fama and French (2002); Lemmon and Zender (2004); and Strebulaev and Yang (2013) treat dividend paying firms separately by imposing certain conditions on these firms in their empirical analysis. They justify this separation between zero-dividend paying and dividend paying firms by arguing that it is better for testing the implications of the pecking order theory(Myers, 1984). In addition, as argued by Strebulaev and Yang (2013) this separation allows distinguishing between high growth firms and cash cows.

4.4. Univariate Analysis

In this section I provide detailed univariate analysis for a number of variables that empirically test the theoretical implications discussed in the previous section. T-tests are carried out for variables representing the firm's capital constraints, valuation and financing activities, investment opportunities and profitability, and dividend payments.

4.4.1. Borrowing Constraints

Different measures have been used in the literature to test for the firm's borrowing ability and the difficulties facing it. For example, Strebulaev and Yang (2013) use cash flow, tangible assets, and credit rating of the firm and they set firm size as a control proxy. Since this study focuses on SMEs and more specifically on the differences between micro, small and medium SMEs, I divide my sample into three size categories, namely, micro, small, and medium and compare the variables used between debt and debt-free SMEs within each size segment and then for the whole SMEs sample. Furthermore, I proxy the firm's borrowing constraints through a set of variables namely, capital intensity ratio (CI), cash holdings (Cash), tangible assets (TA), and S&P long term credit ratings (CRATING)[16].

The cash holding ratio is constructed by dividing cash and marketable securities by total assets. Previous literature such as Calomiris et al. (1995) and Almeida et al. (2011) argue that a relatively high level of cash in the balance sheets indicates a higher level of constraint facing the firms. Those firms try to avoid the high costs of any possible future default on their payments by accumulating cash as a precautionary saving. Furthermore, several studies such as Opler et al. (1999), Graham (2000) and Strebulaev and Yang (2013) find that firms with higher cash holdings prefer to use less debt to a point that debt-free firms could desire to have negative debt to the extent that increasing cash is a substitute for negative debt[17].

From the fourth column of table 4.4, it is noticed that debt-free SMEs across the different size segments hold significantly higher levels of cash in their balance sheets (between 24.04% and 35.22%) compared to debt SMEs (between 10.92% and 15.04%), so a negative relationship can be noted between cash holdings and debt levels. Moreover, there is a negative relationship between debt-free SMEs and SMEs size where the level of cash holdings decreases from micro to medium SMEs. This may be explained by the unstable financial nature of micro SMEs, such that they need to keep higher levels of cash to face any sudden payments.

My second proxy for capital constraints is Tangible assets. SMEs are more likely to suffer from moral hazards and adverse selection problems (Sogorb-Mira, 2005). Therefore the collateral value of their assets plays a role in mitigating such problems.

[16] Details about the variables construction can be found in table 4.17

[17] In some studies (e.g. Almeida and Campello (2007), Gamba and Triantis (2008)) cash can be viewed as a negative debt where net debt can be defined as book value of debt minus cash.

This idea is further supported with theoretical and empirical evidence such as Chittenden et al. (1996), Whited (1992), and Hall et al. (2000). Fama and French (2002) and Frank and Goyal (2008) think of tangible assets as collateral supporting the firm's debt financing. Therefore, I believe that SMEs with less tangible assets tend to become debt-free SMEs compared to SMEs with more tangible assets.

Column 5 of table 4.4 reports a significant difference for the means of TA between debt and debt-free SMEs across various size segments where the debt-free SMEs have 13.65% of tangible assets relative to their total assets, whereas the debt SMEs have around 26.60% of tangible assets. As discussed above the findings support the notion that debt-free SMEs provide less tangible assets and hence suffer from more constraints on borrowing. It is also noted that within the debt SMEs, micro SMEs have the highest percentage of tangible assets compared to small and medium SMEs, with 29.38%, 25.19%, and 25.39% for micro, small, and medium SMEs respectively. This can be explained by the need of micro SMEs to mitigate the higher level of cash flow uncertainty, moral hazard and adverse selection problems by providing higher levels of tangible assets as collateral for their debts.

The third proxy used is the capital intensity ratio, which is defined as fixed assets divided by the number of employees adjusted by the industry median based on 3-digit SIC. This proxy indicates that low capital intensive SMEs tend to have high fixed costs of employee compensation and high incentive costs of employees in cases of financial distress (Babenko, 2004). Thus, low capital intensive SMEs are considered to be more constrained than high capital intensive SMEs. According to MacKay and Phillips (2002) capital intensive firms use more debt than do labour intensive firms. Therefore, firms with high labour intensity (low capital intensity) are more likely to become debt-free. According to column 6 in table 4.4 this argument holds, where debt SMEs have significantly higher mean (0.3083) than their debt-free counterparts with 0.1176. Thus, labour-intensive SMEs are more closely associated with debt-free capital structure than are capital-intensive SMEs. Moreover, this argument can be further supported by the findings of each SMEs size segment, where the means of capital intensity reported for debt SMEs are significantly higher than the means of debt-free SMEs.

In line with previous literature such as Strebulaev and Yang (2013) and Faulkender and Petersen (2006) firm credit ratings can be used as a proxy for access to the public debt markets. They find higher leverage ratios for firms with credit ratings compared to firms without credit ratings.

For the S&P long term credit ratings I construct two variables as per Strebulaev and Yang (2013). First, the long rating dummy equals one if the SME has a credit rating and zero otherwise. Second, for the SMEs that have credit ratings, I construct an Investment-Grade variable that equals one if the SME has an investment grade rating (BBB- or higher) and zero otherwise.

In general, it is expected that most SMEs do not have credit ratings due to their small size and specific structure. Moreover, the results provided in table 4.4, column 9 show that debt-free SMEs are significantly less likely to have a credit rating compared to debt SMEs (only 0.19% of debt-free SMEs' have credit rating, compared to 1.34% for debt SMEs). This implies that debt-free SMEs access to public markets is hugely restricted. Conditional on having a credit rating, the average ratings for debt-free SMEs are not significantly different from those of debt SMEs throughout the three size segments.

Furthermore, I have used the KZ index to measure the SMEs' reliance on external equity financing. SMEs with a higher KZ index are more likely to experience difficulties when using equity financing. The KZ index is estimated using the Baker et al. (2003) method, provided in table 4.17. The 10th column in table 4.4 indicates that a significant difference exists between debt-free and debt SMEs, with debt SMEs being more exposed to equity financing constraints with a KZ index of -1.81, compared to debt-free SMEs with KZ index of -2.88. Therefore, debt-free SMEs use more equity financing compared to debt financing and so have a greater opportunity to become debt-free.

However, the difference in average means between debt and debt-free micro SMEs is insignificant, with both groups having relatively lower means of KZ scores, around -3.6, compared to the SMEs sample. This might indicate more access to equity financing rather than debt, which supports the findings in table 4.1 that micro SMEs tend to have a higher percentage of debt-free firms.

The findings for small and medium SMEs record significant differences between the average means of debt and debt-free SMEs. Finally, it can be noticed that the KZ score increases across the different size segments, suggesting that the larger the SME the more it prefers to use debt rather than equity and hence become a debt SME. Therefore, it can be inferred that equity markets are relatively more attractive for debt-free SMEs compared to debt markets, and this preference for equity markets has a negative relationship with the SMEs' size.

Table 4.4 financing constraints

This table provides mean comparison tests between debt and debt-free SMEs across the different size segments for borrowing constraints proxies. Cash holdings represent the cash and marketable securities divided by total assets. Tangible assets are property, plant and equipment divided by total assets. Capital Intensity is the fixed assets divided by total number of employees. Credit rating dummy is equal to one if the SME has a long term credit rating and zero otherwise. Inves. Grade equals one if the SME has an investment-grade rating (BBB- or higher) and zero otherwise. # of obs. is the number of SMEs with credit rating. KZ index is constructed according to Baker et al. (2003).

Size (1)	(2)	# of Obs. (3)	Cash (4)	TA (5)	CI (6)	CREDIT (7)	Inves. Grade (8)	# of Obs. (9)	KZ Index (10)
Micro	Debt	24109	0.1504	0.2938	0.7611	0.0147	0.0891	359	-3.7937
	Debt-Free	8135	0.3522	0.1511	0.2159	0.0009	0.0000	7	-3.5857
	P value		0.0000	0.0000	0.0000	0.0000	0.4097		0.2641
Small	Debt	21202	0.1498	0.2519	0.1508	0.0047	0.0101	99	-1.0233
	Debt-Free	5028	0.3189	0.1188	0.0712	0.0018	0.0000	9	-2.5990
	P value		0.0000	0.0000	0.0000	0.0041	0.7646		0.0000
Medium	Debt	31092	0.1092	0.2539	0.0809	0.0184	0.0332	573	-0.8104
	Debt-Free	5577	0.2404	0.1312	0.0325	0.0036	0.1000	20	-2.1174
	P value		0.0000	0.0000	0.0000	0.0000	0.1122		0.0000
SMEs	Debt	76686	0.1335	0.2660	0.3083	0.0134	0.0504	1031	-1.8145
	Debt-Free	18764	0.3101	0.1365	0.1176	0.0019	0.0556	36	-2.8811
	P value		0.0000	0.0000	0.0000	0.0000	0.8906		0.0000

4.4.2. SMEs' Valuation and Financing Activities

In order to test the effect of SMEs valuation and Financing Activities on the capital structure decisions for SMEs I use several proxies such as market to book ratio (MB), net debt issues (NDI), net equity issues (NEI), and changes in market equity (CME).

Market to book ratio (MB) is one of the most frequently used measures in the capital structure research as a measure of equity market valuation of the firm. It is argued that the level of debt decreases when the firm enjoys a higher level of MB (Kayhan and Titman, 2007). Table 4.6 supports this argument and shows that debt-free firms enjoy significantly higher mean of MB value (5.88) compared to debt firms (4.67). Similar findings can be found for micro and medium SMEs. However, small SMEs show insignificant difference between the MB means of debt and debt-free SMEs, hence MB does not seem to affect small SMEs decisions for debt financing.

Furthermore, since a number of theoretical explanations for the debt-free puzzle are dynamic in nature, I test NDI, NEI, and CME for debt-free SMEs relative to debt SMEs over five years prior to and after the debt-free year. I also compare and contrast these patterns with those for debt SMEs. Table 4.5 presents the results of financing activities for debt-free and debt SMEs in addition to the three size segments. In the debt-free year (year=0), the net-equity issuance for debt-free SMEs across the different size segments is higher than for debt SMEs, suggesting a high reliance of debt-free SMEs on using equity rather than debt financing. However, this reliance on equity issuance decreases after the event year for debt-free SMEs coupled with a similar decrease for the debt SMEs along the five years after the event, but it can be noticed that even after five years of being debt-free, the reliance on equity issuance is higher than for their counterparts.

This can be further supported by the results reported about net debt issuance, where debt-free SMEs decrease their debt levels for several years prior to becoming debt-free until the net debt issuance reaches a negative value for debt-free SMEs in the year of the event, indicating a difficulty in accessing debt markets. On the other hand debt SMEs attain their peak of debt use in the event year. After the event year, debt-free SMEs are able to access the debt markets and increase their debt levels to around (3.2%) and gradually increase their debt usage over time.

Furthermore, changes in market value of equity increase over the 5 years period for debt-free SMEs until they attain debt-free status. Afterwards the CME slightly decreases over time. These findings can be better illustrated in figure 4.1 showing the movement of NEI, NDI, and CME over 5 years prior to and after the debt-free event.

Figure 4.1 net equity issuance, net debt issuance, and change in market equity

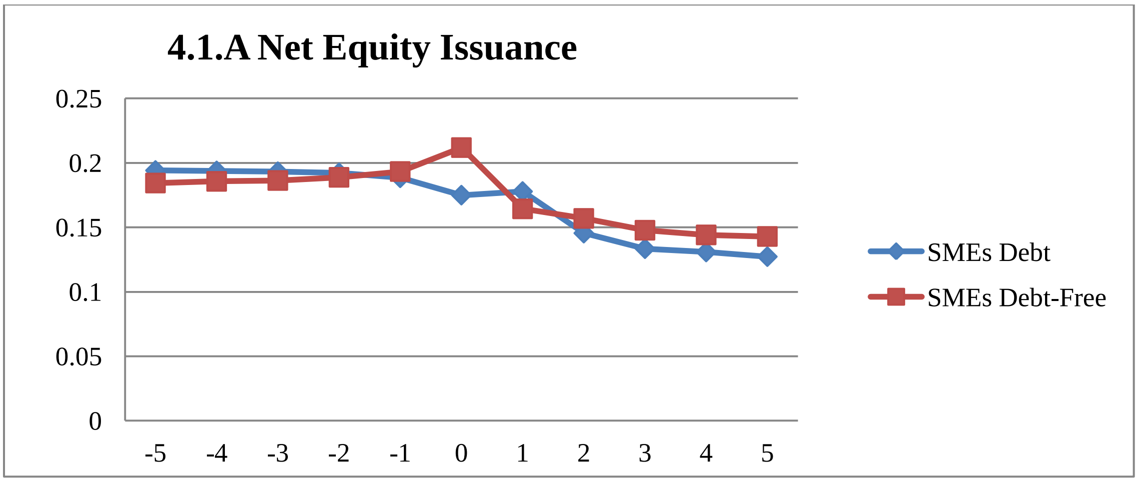


Figure 4.1.A This figure reports the net equity issuance value for debt and debt-free SMEs around the debt-free year which is given a value of zero in this figure. The x axis represents the period around the event time where the time zero indicates the event time, and five years prior to and after the event time are reported. The y axis indicates the value of the net equity issuance for both debt and debt-free SMEs. The net equity issuance variable is constructed as: Sales of common and preferred stocks – purchase of common and preferred stocks.

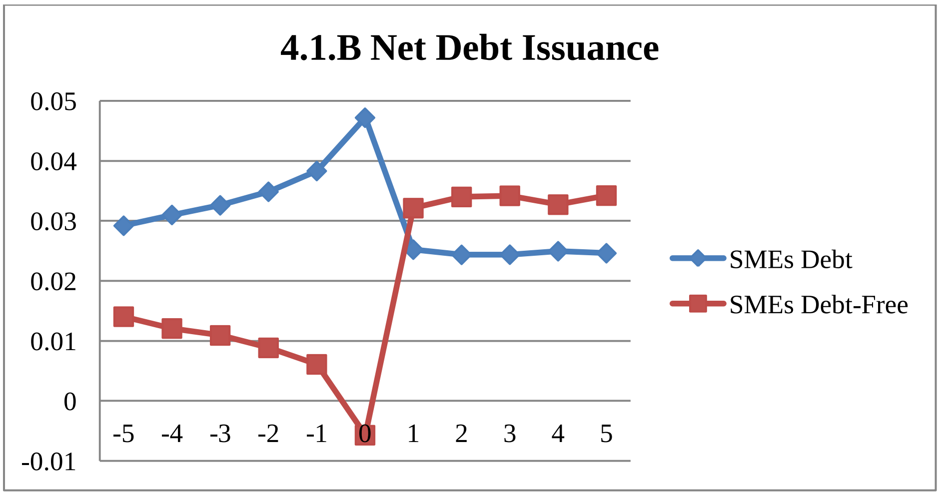


Figure 4.1.B This figure reports the net debt issuance value for debt and debt-free SMEs around the debt-free year which is given a value of zero in this figure. The x axis represents the period around the event time where the time zero indicates the event time, and five years prior to and after the event time are reported. The y axis indicates the value of the net debt issuance for both debt and debt-free SMEs. The net debt issuance variable is constructed as: Long term debt issuance – long term debt reduction + current debt changes.

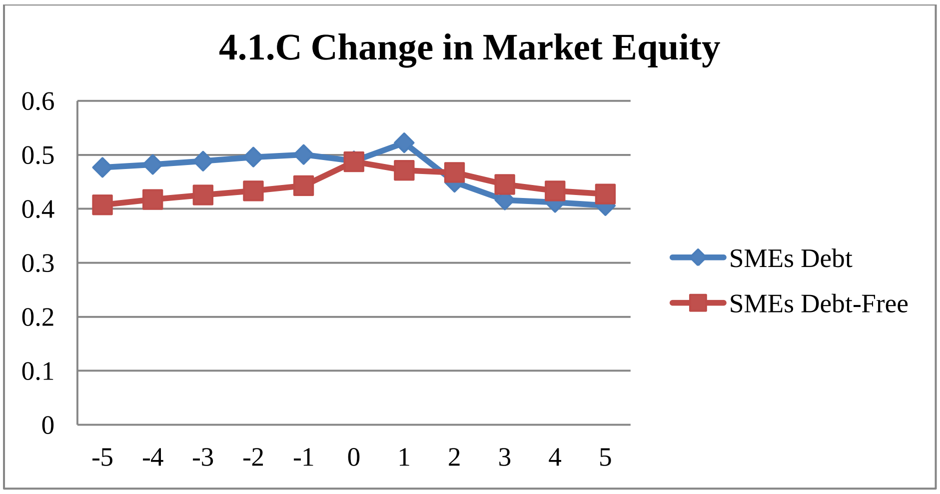


Figure 4.1.C This figure reports the changes in market equity for debt and debt-free SMEs around the debt-free year which is given a value of zero in this figure. The x axis represents the period around the event time where the time zero indicates the event time, and five years prior to and after the event time are reported. The y axis indicates the percentage of the change in market value of equity for both debt and debt-free SMEs. The change in market value of equity variable is constructed as: the percentage change between the market value of equity for in year (t) compared to year (t-1).

Table 4.5 financing activities relative to debt-free year
This table presents the financing activities for debt-free and debt SMEs over time, in addition to the three size segments namely micro, small, and medium SMEs. NEI indicates net equity issuance. NDI indicates net debt issuance. CME indicates the change in market value of equity

Size			-5	-4	-3	-2	-1	0	1	2	3	4	5
Micro	NEI	Debt	0.2595	0.2626	0.2610	0.2640	0.2622	0.2376	0.2325	0.1980	0.1867	0.1829	0.1760
		Debt-Free	0.2355	0.2360	0.2382	0.2404	0.2410	0.2686	0.2076	0.2036	0.2004	0.1954	0.1957
Small	NEI	Debt	0.2185	0.2134	0.2148	0.2121	0.2067	0.1954	0.2052	0.1700	0.1595	0.1572	0.1528
		Debt-Free	0.2062	0.2063	0.2065	0.2112	0.2192	0.2367	0.1934	0.1824	0.1693	0.1659	0.1611
Medium	NEI	Debt	0.0980	0.1014	0.1027	0.1036	0.1035	0.1019	0.1127	0.0862	0.0718	0.0688	0.0678
		Debt-Free	0.1036	0.1044	0.1057	0.1060	0.1096	0.1127	0.0865	0.0822	0.0712	0.0707	0.0712
SMEs	NEI	Debt	0.1941	0.1938	0.1932	0.1923	0.1885	0.1750	0.1778	0.1455	0.1334	0.1309	0.1273
		Debt-Free	0.1844	0.1857	0.1864	0.1888	0.1933	0.2119	0.1644	0.1569	0.1478	0.1441	0.1429
Micro	NDI	Debt	0.0567	0.0606	0.0646	0.0678	0.0746	0.0944	0.0634	0.0593	0.0581	0.0593	0.0579
		Debt-Free	0.0330	0.0303	0.0283	0.0262	0.0215	-0.0003	0.0458	0.0527	0.0549	0.0536	0.0596
Small	NDI	Debt	0.0183	0.0209	0.0225	0.0249	0.0281	0.0344	0.0166	0.0163	0.0165	0.0173	0.0172
		Debt-Free	0.0088	0.0062	0.0046	0.0020	-0.0004	-0.0083	0.0286	0.0304	0.0288	0.0268	0.0255
Medium	NDI	Debt	0.0108	0.0099	0.0098	0.0121	0.0135	0.0159	0.0027	0.0048	0.0054	0.0049	0.0050
		Debt-Free	-0.0016	-0.0024	-0.0031	-0.0060	-0.0076	-0.0106	0.0191	0.0168	0.0171	0.0166	0.0163
SMEs	NDI	Debt	0.0292	0.0310	0.0326	0.0349	0.0383	0.0472	0.0252	0.0244	0.0244	0.0250	0.0246
		Debt-Free	0.0140	0.0121	0.0109	0.0089	0.0061	-0.0057	0.0321	0.0340	0.0342	0.0327	0.0342
Micro	CME	Debt	0.7593	0.7783	0.7856	0.8116	0.8361	0.8208	0.9022	0.8266	0.7955	0.7948	0.7880

		Debt-Free	0.5714	0.5890	0.6145	0.6284	0.6245	0.6973	0.7394	0.7790	0.7878	0.7643	0.7509
Small	CME	Debt	0.4667	0.4628	0.4775	0.4797	0.4767	0.4642	0.4909	0.4151	0.3910	0.3854	0.3703
		Debt-Free	0.4149	0.4271	0.4105	0.4115	0.4273	0.4544	0.4311	0.4137	0.3731	0.3670	0.3740
Medium	CME	Debt	0.2006	0.2111	0.2189	0.2278	0.2360	0.2368	0.2626	0.2020	0.1579	0.1463	0.1465
		Debt-Free	0.2324	0.2320	0.2413	0.2389	0.2468	0.2597	0.1989	0.1835	0.1535	0.1581	0.1465
SMEs	CME	Debt	0.4766	0.4821	0.4883	0.4958	0.5005	0.4887	0.5223	0.4491	0.4164	0.4117	0.4058
		Debt-Free	0.4073	0.4172	0.4255	0.4332	0.4428	0.4871	0.4712	0.4673	0.4450	0.4331	0.4273

4.4.3. Investment Opportunities and Profitability

As discussed in section 4.3, it is believed that profitable SMEs tend to borrow less debt since they are able to generate sufficient cash flow to cover their financing. As a consequence, profitable SMEs tend to become debt-free relying only on internally generated cash. In addition, I hypothesise that debt-free SMEs have more investment opportunities compared to debt SMEs since they tend to reduce the likelihood of issuing risky securities in order not to forgo profitable future investment opportunities. To test the above two hypotheses I use operating cash flow (OCF), free cash flow (FCF), operating cash flow deficit (NIOCF), and cash flow deficit (NIFCF) as measures of SMEs' profitability. SMEs' investment opportunities are proxied by using R&D expenses (RD), MB ratio (MB), advertising expenses (AD), and net investment (NI).

Panel A of table 4.6 provides the results for the profitability proxies. A surprising result is that operating cash flows are significantly lower for debt-free SMEs for the whole sample and in each size segment compared to the debt SMEs. However, free cash flows show fluctuating patterns across size, where the average means of small and medium debt free SMEs are higher than their debt SMEs counterparts, but significantly lower for the whole SMEs sample. Moreover, the cash flow deficit is significantly larger for debt-free SMEs across the size segments, suggesting that debt-free SMEs invest more than internally generated funds. Furthermore, I notice the cash flow deficit decreases when the SMEs' size increases implying that larger SMEs tend to balance their investments with the cash flows generated. These results provide evidence that debt-free SMEs become debt-free by relying solely on external equity. Panel B of table 4.6 shows the results of the investment opportunity proxies. The net investment proxy provides mixed results, on the one hand, the net investment is significantly lower for debt-free micro and whole sample SMEs compared to their debt counterparts. On the other hand, the net investment for debt-free medium SMEs is significantly higher than for debt medium

SMEs. Moreover, except for small size SMEs, the market to book ratio (MB) is significantly higher for debt-free SMEs. The table further shows that R&D expenses are significantly higher for debt-free SMEs across the size samples. In contrast, the advertising expenses for debt-free SMEs are less than debt SMEs for all size segments except for medium SMEs, where the results are insignificant. From these findings, it can be generalized that debt-free SMEs face lower capital expenditure (tangible expenses) and advertising expenses but greater R&D expenses (intangible expenses) compared to debt SMEs.

Table 4.6 investment opportunity and profitability
This table provides mean comparison tests between debt and debt-free SMEs across the different size segments for investment opportunity and profitability. OCF is the operating cash flow divided by total assets. FCF is the free cash flow divided by total assets. NI is the net investment divided by total assets. NIFCF is the difference between NI and FCF. NIOCF is the difference between net investment and operating cash flow. RD is the research and development expenses divided by total assets. AD is the advertising expenses divided by total assets.

			Panel (A) Profitability				Panel (B) Investment Opportunity			
Size		# of Obs.	OCF	FCF	NIFCF	NIOCF	NI	MB	RD	AD
Micro	Debt	24109	-0.1530	-0.4446	0.5540	0.2613	0.1083	9.0113	0.0862	0.0074
	Debt-Free	8135	-0.2001	-0.4476	0.5283	0.2803	0.0802	9.5952	0.0978	0.0041
	P value		0.0000	0.7493	0.0053	0.0000	0.0000	0.0000	0.0000	0.0000
Small	Debt	21202	-0.1074	-0.2042	0.3034	0.2065	0.0991	3.9077	0.1017	0.0095
	Debt-Free	5028	-0.1379	-0.1935	0.2874	0.2317	0.0938	3.8492	0.1508	0.0077
	P value		0.0000	0.1422	0.0345	0.0000	0.0305	0.4843	0.0000	0.0000
Medium	Debt	31092	0.0189	-0.0036	0.1047	0.0821	0.1010	2.1276	0.0638	0.0094
	Debt-Free	5577	0.0041	0.0049	0.1106	0.1113	0.1154	2.5988	0.1111	0.0094
	P value		0.0000	0.0108	0.1260	0.0000	0.0000	0.0000	0.0000	0.9829
SMEs	Debt	76686	-0.0707	-0.1985	0.3017	0.1735	0.1028	4.6726	0.0814	0.0088
	Debt-Free	18764	-0.1227	-0.2444	0.3390	0.2171	0.0943	5.8805	0.1160	0.0067
	P value		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4.4.4. Dividend Payments

This sub-section tests whether debt-free SMEs pay higher dividends than debt SMEs as a substitute for leverage. Furthermore, I examine whether more dividends are paid by debt-free high growth SMEs since those SMEs have the motive to satisfy shareholders so that they can raise external equity on favourable terms, thus effectively replacing payouts to debt-holders with payout to equity holders and without the adverse effects of the agency problem of debt.

The data in table 4.7 confirm my hypothesis that debt-free SMEs pay significantly higher dividends than debt SMEs across the different size segments, with a dividend ratio of 0.014 for debt-free SMEs and 0.010 for debt SMEs. Surprisingly, my results show that debt free micro SMEs pay much more dividends (0.016) than small, medium, and whole SMEs groups, which pay 0.013, 0.014, and 0.014 respectively. It is puzzling that micro SMEs do not generate high free cash flows compared to other groups, yet they pay a larger amount of dividends.

One possible explanation for the high level of dividend payment by micro SMEs is that mentioned by La Porta et al. (2000) which states that small firms pay more dividends in order to build a reputation for addressing the agency problem of expropriating outside shareholders, which helps them raise external equity on favourable terms. This argument is further supported by Gomes (2000) who finds that small, growing debt-free firms pay more dividends as they become exclusively equity dependant.

On the other hand, the higher dividend payments made by larger debt-free SMEs (small and medium) compared to their counterpart debt SMEs can be explained by the desire of large debt-free SMEs to mitigate the agency costs of free cash flow due to their low usage of leverage. In addition, according to column 5 of table 4.6, the free cash flows of small and medium debt-free SMEs are higher compared to small and medium debt SMEs which might increase the agency cost problem of free cash flow hence they use the additional cash flow generated to pay dividends while reducing the existing debt to become debt-free, keeping their equity valuation intact, due to shareholders' concern for the agency costs of free cash flow.

Table 4.7 dividend payments
This table provides mean comparison tests between debt and debt-free SMEs across the different size segments for dividend payments. DR represents Dividend ratio which is cash dividends divided by total assets.

Size		# of Obs.	DR
Micro	Debt	24109	0.0142
	Debt-Free	8135	0.0164
	P value		0.0034
Small	Debt	21202	0.0114
	Debt-Free	5028	0.0139
	P value		0.0008
Medium	Debt	31092	0.0067
	Debt-Free	5577	0.0114
	P value		0.0000
SMEs	Debt	76686	0.0104
	Debt-Free	18764	0.0142
	P value		0.0000

4.5. Further Investigation of Debt-Free Behaviour

This section provides additional empirical analysis as to why SMEs may become debt-free.

4.5.1. Non-debt tax shield, Pension Obligations and Lease Commitments

Researchers such as Graham (2000) and Strebulaev and Yang (2013) pose the question: how much in tax benefits can debt-free firms potentially get if they increase their leverage? In other words, how much money do they leave on the table by not levering up? Therefore, the potential tax benefit will be limited for debt-free firms if the marginal tax rate is close to zero. In addition, new evidence is found by Graham and Tucker (2006) that US firms are using non-debt tax shield (NDTS) alternatives and that engagement in tax shelter activities leads to a reduction in their debt levels. According to the DeAngelo and Masulis (1980) model, NDTS substitutes for interest tax deduction and firms with higher NDTS tend to become debt-free firms. In order to proxy for tax shelters used by SMEs in my sample, a non-debt tax shield (NDTS) is constructed in order to test if any tax differences exist between the debt and debt-free SMEs.

Another economic mechanism that might explain zero-debt behaviour is the use of pension and health care liabilities that potentially constitute an important debt substitute. Stefanescu (2006) finds that pension plans have debt-like features in that pension contributions are tax deductible. Shivdasani and Stefanescu (2010) point out that tax deductions of pension contributions equal about one-third of those of debt interest payments. However if these liabilities are not adjusted properly it might lead to bankruptcies, as in the case of GM and United Airlines. To proxy for pension liabilities I follow the definition provided by Shivdasani and Stefanescu (2010), who define pension obligations as the sum of Projected Pension Obligations (PBPRO) and Projected Pension Obligations (Underfunded) (PBPRU), and pension assets as the sum of Pension Plan Assets (PPLAO) and Pension Plan Assets (Underfunded) (PPLAU).

Then I adopt Strebulaev and Yang's (2013) definition of Net Pension Liabilities as the difference between pension obligations and pension assets if pension obligations are greater than or equal to pension assets and as zero otherwise. Then I use Net Pension Liabilities (NPL) as a proxy for the extent of tax deductibility of pension plans.

Since non-debt tax shields and off-balance-sheet liabilities provide tax deductions from non-debt sources, hence it can be inferred that debt-free SMEs are more willing to use them than debt SMEs.

Table 4.8 shows that non-debt tax shields of debt-free SMEs are significantly lower than those of debt SMEs for the whole sample and across each size segment, where the NDTS is 0.0463 for debt-free SMEs and 0.0675 for debt SMEs. Interestingly, the results show that debt-free SMEs have significantly less net pension liabilities than other SMEs. According to Strebulaev and Yang (2013) this can be explained by the fact that large unfunded pension plans are also typically highly levered and economic factors that lead to higher debt usage are also likely to contribute to larger pension liabilities. These findings suggest that both NTDS and NPL are unlikely to play a major role in explaining debt-free policy.

Recently, the topic of operating leases has gained importance in the capital structure studies. It has been suggested by Rampini and Viswanathan (2010) and Rauh and Sufi (2012) that the capitalized value of operating leases should be included in total debt valuation. However, operating leases can both complement traditional debt and play the role of its substitute (Lewis and Schallheim, 1992; Graham et al., 1998; Yan, 2006; Eisfeldt and Rampini, 2009). Therefore, it is believed that debt-free SMEs have higher operating leases in their balance-sheets compared with their debt counterparts. I use 1 and 5 years operating leases ratio as proxies for operating leases. The results provided in table 4.8 show that both OL1 and OL5 are significantly lower for debt-free

SMEs than they are for debt SMEs across various size levels and therefore operating leases are unlikely to explain debt-free policy.

Table 4.8 non-debt tax shield, pensions, and lease commitments
This table provides mean comparison tests between debt and debt-free SMEs across the different size segments for Non-debt tax shield, pensions, and lease commitments. NDTS (net-debt tax shields) are depreciation, amortization, deferred tax, and investment tax credit divided by total assets. NPL is the net pension liabilities defined as the difference between pension obligations and pension assets if pension obligations are greater than or equal to pension assets and as zero otherwise. OL1 and OL5 are one and five years operating lease commitments.

Size		# of Obs.	NDTS	NPL	OL1	OL5
Micro	Debt	24109	0.0760	0.0026	0.0287	0.0866
	Debt-Free	8135	0.0461	0.0008	0.0153	0.0433
	P Value		0.0000	0.0000	0.0000	0.0000
Small	Debt	21202	0.0658	0.0024	0.0338	0.1041
	Debt-Free	5028	0.0435	0.0020	0.0271	0.0822
	P Value		0.0000	0.2191	0.0000	0.0000
Medium	Debt	31092	0.0621	0.0072	0.0298	0.1011
	Debt-Free	5577	0.0491	0.0043	0.0268	0.0890
	P Value		0.0000	0.0000	0.0000	0.0000
SMEs	Debt	76686	0.0675	0.0044	0.0306	0.0973
	Debt-Free	18764	0.0463	0.0022	0.0219	0.0673
	P Value		0.0000	0.0000	0.0000	0.0000

4.5.2. Debt-Free Vs. Low-Debt Puzzles

Strebulaev and Yang (2013) argue that the low-leverage puzzle is an artefact of the debt-free puzzle and they are closely connected. However, the existing models of capital structure produce a relatively high "lowest leverage ratio" under most of the cases they consider. Leland (1994) produced a leverage ratio of 70-90% under reasonable parameters, while Goldstein et al. (2001) set the lowest leverage ratio at 34%. Recently, using the endogenous investment models and models that introduce fixed costs into the dynamic capital structure the optimal leverage ratios have been set much lower. For example, Hackbarth and Mauer (2011) find the optimal leverage ratio to be only 12%. In spite of this enhancement of the capital structure models, Graham (2003) and Strebulaev and Yang (2013) criticize the inability of these models to explain the presence of debt-free or low-debt firms in the economy.

To have a better understanding of the average leverage levels in my SMEs sample, table 4.9 reports the mean and median values of debt ratios for my total sample, the sample excluding debt-free SMEs, and the sample excluding low-debt SMEs using both book and market leverage ratios. Book and market debt definitions are in line with Graham and Leary (2011); Lemmon and Zender (2004) and Strebulaev and Yang (2013) which are widely used definitions in capital structure research[18].

It can be observed that the book (Market) leverage ratio of an average SME for my sample during the period from 1980 to 2014 is 26% (15%) which is less than the optimal leverage ratio suggested in many capital structure models. When excluding the debt-free SMEs from the sample the mean increases to 32% (19%) for book (Market) leverage. This percentage further increases when excluding the low-debt ratio to reach 38% (22%). This final percentage of mean book leverage is very similar to the optimal level of debt suggested by Goldstein et al. (2001). The fact that I have excluded both

[18] More details about book and market debt definitions can be found in the table 4.17

debt-free and low-debt SMEs in order to achieve the optimal debt level indicates that these models are not yet able to explain low-debt behaviour and this puzzling behaviour cannot be explained by normally levered SMEs but only by extremely low-levered SMEs, and this result is very similar to that of Strebulaev and Yang (2013) for large firms.

Table 4.9 market vs. book debts
This table reports the means of debt ratios for the total sample, the sample excluding debt-free SMEs, and the sample excluding low-debt SMEs. Columns 1 and 2 report market debt; Columns 3 and 4 report book debt.

		Market Debt			Book Debt		
Size		# Obs.	Mean	Median	# Obs.	Mean	Median
Micro	All Sample	28862	13%	4%	32345	23%	16%
	Excluding DFREE SMEs	21278	18%	10%	24186	27%	22%
	Excluding LDEBT SMEs	18357	20%	13%	20971	33%	29%
Small	All Sample	25492	14%	6%	26162	24%	15%
	Excluding DFREE SMEs	20547	17%	10%	21134	30%	24%
	Excluding LDEBT SMEs	16538	21%	15%	17056	36%	31%
Medium	All Sample	35614	17%	10%	36542	31%	20%
	Excluding DFREE SMEs	30090	20%	14%	30965	41%	37%
	Excluding LDEBT SMEs	24053	25%	20%	24868	47%	45%
SMEs	All Sample	89968	15%	6%	95049	26%	17%
	Excluding DFREE SMEs	71915	19%	12%	76285	32%	26%
	Excluding LDEBT SMEs	58948	22%	17%	62895	38%	34%

4.5.3. Future Investments

According to the dynamic capital structure models, it can be argued that firms may follow a debt-free policy or lower their leverage in order to retain financial flexibility in anticipation of future investments (Goldstein et al., 2001). In order to see how debt-free SMEs may change their capital expenditure around the debt-free year I need to study the behaviour of certain variables and particularly how they change around the debt-free years. In table 4.10 I provide a time scale of five years before and after the event year[19] that captures the movements of certain variables around the event year.

Therefore, to examine the effect of future investment, I construct an abnormal investment proxy following Titman et al. (2004)[20]. Table 4.10 shows that debt-free SMEs under-invest compared with their debt counterparts. Furthermore, future investments for debt-free SMEs decline over time until they reach the debt-free year. This declining nature can also be observed across the three size categories of SMEs.

Furthermore, I study book leverage ratio and capital expenditure around the debt-free year. Table 4.10 and figure 4.2 show that debt-free SMEs adopt a persistent conservative debt policy prior to becoming debt-free. Furthermore, the debt-free SMEs maintain consistently lower leverage than the levered SMEs. In addition, the leverage levels for debt SMEs continuously increase year by year whereas the debt-free SMEs tend to decrease their reliance on debt when approaching the event year. However, after the event year, debt-free SMEs start increasing their debt levels rapidly over the following years whereas the debt SMEs slightly decrease their reliance on debt.

Figure 4.2.C about capital expenditure confirms my findings in figure 4.2.A that debt-free SMEs underinvest compared to their levered counterparts. However the difference

[19] The event year is the debt-free year in the debt-free sample and the debt year within the debt sample. In each of the years relative to the debt-free year, I include all available firms that survive from the prior years to the debt-free year. I apply the same criteria for debt firms. For firms with consecutive debt-free years, I examine five years prior to the first debt-free year. I exclude firms that are debt-free for their entire sample periods.

[20] Definition is provided in table 4.17

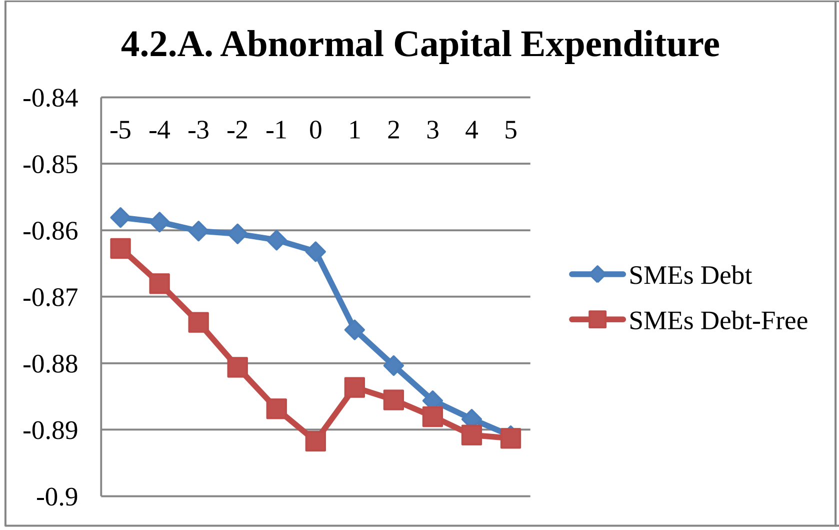
in their relative investments decreases steadily after the debt-free year and consequently becomes negligible. An interesting finding is that debt-free SMEs in the year t+1 increase their investment level which is linked with a substantial increase in their debt levels for the same year. This can be explained by the financial flexibility and underinvestment hypothesis that by strategically reducing debt, debt-free SMEs are able to mitigate investment distortions. This finding is also in line with the results of Dang (2013).

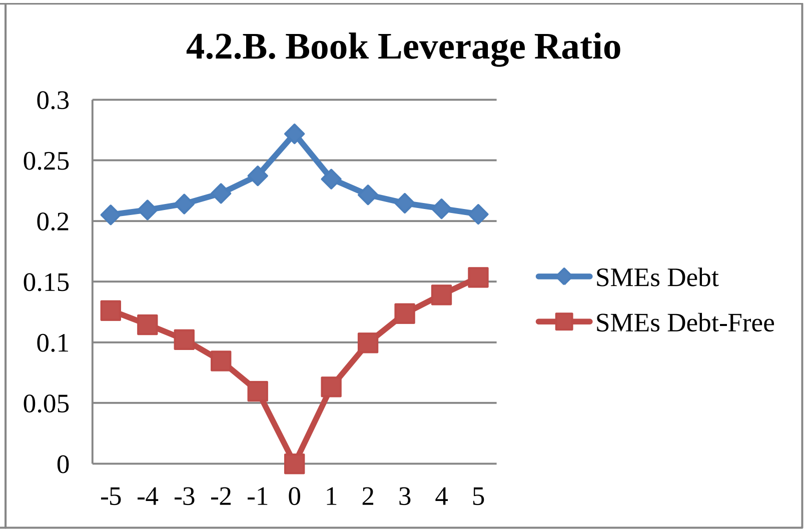
Table 4.10 future investment over time
This table presents the future investment behaviour for debt-free and debt SMEs over time, in addition to the three size segments namely micro, small, and medium SMEs. ABCE represents the abnormal investment. BLR is the book leverage ratio defined as total debt divided by total assets. CETA is the capital expenditure divided by total assets.

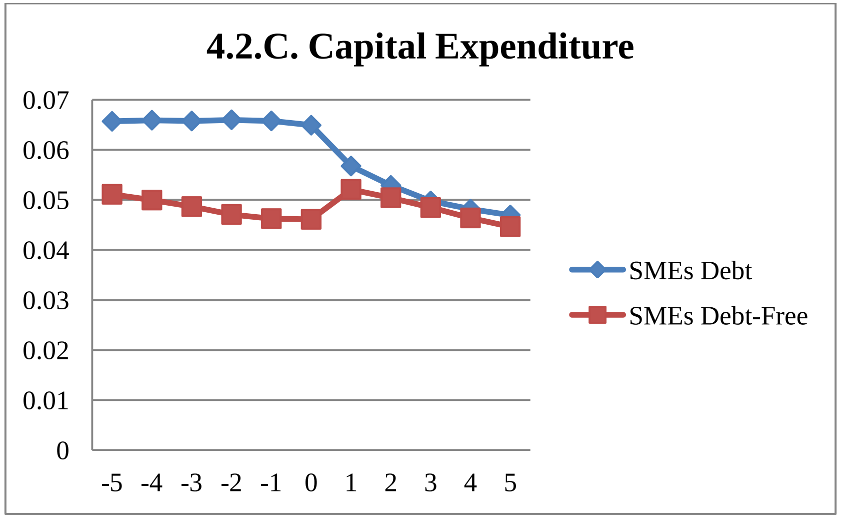
Size			-5	-4	-3	-2	-1	0	1	2	3	4	5
Micro	ABCE	Debt	-0.8724	-0.8718	-0.8718	-0.8718	-0.8725	-0.8716	-0.8949	-0.9053	-0.911	-0.9134	-0.9165
		Debt-Free	-0.8575	-0.8623	-0.8669	-0.8733	-0.8786	-0.8816	-0.9019	-0.904	-0.9087	-0.912	-0.9129
Small	ABCE	Debt	-0.8517	-0.8529	-0.8549	-0.8535	-0.8554	-0.8593	-0.8687	-0.8719	-0.8777	-0.8812	-0.8831
		Debt-Free	-0.8573	-0.8622	-0.8674	-0.8755	-0.8798	-0.8803	-0.8706	-0.8763	-0.8787	-0.8816	-0.8828
Medium	ABCE	Debt	-0.8498	-0.8516	-0.8539	-0.8559	-0.8578	-0.8598	-0.8654	-0.8695	-0.8739	-0.8763	-0.8785
		Debt-Free	-0.8732	-0.8789	-0.8858	-0.8912	-0.8992	-0.9079	-0.8756	-0.8754	-0.8765	-0.879	-0.8784
SMEs	ABCE	Debt	-0.8581	-0.8588	-0.8601	-0.8605	-0.8615	-0.8632	-0.875	-0.8803	-0.8856	-0.8884	-0.8909
		Debt-Free	-0.8627	-0.868	-0.8738	-0.8806	-0.8868	-0.8917	-0.8836	-0.8855	-0.888	-0.8908	-0.8913
Micro	BLR	Debt	0.2502	0.2572	0.266	0.2823	0.3088	0.3837	0.3837	0.3085	0.2949	0.2866	0.2784
		Debt-Free	0.1711	0.1585	0.1475	0.1271	0.0946	0	0.0931	0.1432	0.1729	0.1893	0.2107
Small	BLR	Debt	0.1816	0.1866	0.1934	0.2015	0.2149	0.2387	0.214	0.2057	0.2	0.1946	0.1886
		Debt-Free	0.1099	0.0976	0.0827	0.0653	0.0433	0	0.0514	0.0842	0.1055	0.1213	0.1349
Medium	BLR	Debt	0.1811	0.1813	0.1815	0.1849	0.1906	0.2006	0.1787	0.1698	0.1662	0.1643	0.1635
		Debt-Free	0.093	0.0822	0.0687	0.0512	0.0306	0	0.0393	0.0664	0.0885	0.1039	0.1118
SMEs	BLR	Debt	0.2052	0.2092	0.2142	0.2229	0.2374	0.272	0.2347	0.2217	0.2148	0.2102	0.2057
		Debt-Free	0.1263	0.1147	0.1024	0.0848	0.0598	0	0.0634	0.0997	0.1238	0.1392	0.1536
Micro	CETA	Debt	0.0745	0.075	0.0754	0.0761	0.0764	0.0759	0.0612	0.0544	0.0508	0.0488	0.0473

		Debt-Free	0.0575	0.0562	0.0544	0.0518	0.0506	0.0491	0.0567	0.0548	0.0506	0.0489	0.0459
Small	CETA	Debt	0.0628	0.0628	0.0623	0.0634	0.0628	0.0615	0.0552	0.0522	0.0486	0.0472	0.0461
		Debt-Free	0.0459	0.0444	0.0436	0.042	0.0423	0.0435	0.0501	0.0481	0.0473	0.0441	0.0433
Medium	CETA	Debt	0.0591	0.0594	0.0591	0.0585	0.0584	0.0579	0.0546	0.0523	0.0499	0.0484	0.0473
		Debt-Free	0.0491	0.0483	0.0466	0.0459	0.0442	0.0442	0.0484	0.0478	0.0472	0.0458	0.0447
SMEs	CETA	Debt	0.0657	0.0659	0.0657	0.066	0.0658	0.0649	0.0567	0.0529	0.0498	0.0481	0.047
		Debt-Free	0.0511	0.0499	0.0486	0.0471	0.0462	0.0461	0.0521	0.0504	0.0484	0.0464	0.0446

Figure 4.2 abnormal capital expenditure, book leverage ratio and capital expenditure







4.6. Regression Analysis

4.6.1. Correlation Matrix

To examine the possible degree of collinearity among the variables to be included in the final regression models, I have obtained the pairwise correlation matrix which is reported in table 4.11. As I observe in table 4.11, the majority of coefficients among variables are less than (0.5), with a few exceptions being higher than (0.5); e.g. Size and FCF correlation value is 0.5368, CETA and ABCE correlation value is 0.5510. Therefore, the correlation coefficients are not sufficiently large to cause collinearity problems in the regressions.

Table 4.11 correlation matrix

FCF: Free cash flow ratio, CI: Capital Intensity, RD: Research and development ratio, DR: dividend Ratio, TA: Tangible Assets, Age: SME's age according to Compustat listing date, AS: Asset Sale, CETA: capital Expenditure Ratio, ABCE: Abnormal Capital Expenditure, CRATING: Credit Rating, OL5: five years Operating Leases, NPL: Net Pension Liabilities, NDTS: Not-debt Tax Shield. * indicates significance at the 1% level.

	Cash	Size	FCF	CI	RD	DR	TA	AGE	AS	CETA	ABCE	CRATING	OL5	NPL	NDTS
Cash	1														
Size	-0.0901*	1													
FCF	-0.2535*	0.5368*	1												
CI	-0.1068*	0.3172*	0.1003*	1											
RD	0.3264*	-0.0401*	-0.4246*	-0.1163*	1										
DR	0.0670*	-0.0369*	-0.1103*	-0.007	0.0840*	1									
TA	-0.3192*	0.0774*	0.1187*	0.3366*	-0.2109*	-0.0258*	1								
AGE	-0.0590*	0.1237*	0.1147*	-0.0376*	-0.0921*	0.0035	-0.0007	1							
AS	-0.0423*	0.0570*	0.0141*	0.0114*	-0.0168*	-0.0084*	0.0436*	0.0641*	1						
CETA	-0.1316*	0.0084*	0.0163*	0.1549*	-0.0562*	-0.0128*	0.5037*	-0.1819*	0.0570*	1					
ABCE	-0.0692*	0.0424*	0.0028	0.0433*	0.0609*	-0.0058	0.2029*	-0.1648*	-0.0062	0.5510*	1				
CRATING	-0.0472*	0.1752*	0.0480*	0.2520*	-0.0520*	0.0041	0.0757*	0.0426*	0.0162*	0.0263*	-0.0064	1			
OL5	-0.0183*	-0.1136*	-0.1467*	-0.0767*	0.1393*	0.0395*	-0.0193*	-0.0284*	-0.0091*	0.0529*	0.0660*	-0.0311*	1		
NPL	-0.0594*	0.0989*	0.0665*	0.0735*	-0.0610*	-0.0032	0.0199*	0.1620*	-0.0144*	-0.0406*	-0.0114*	0.0523*	-0.0390*	1	
NDTS	-0.1531*	-0.0937*	-0.1432*	0.0957*	0.0400*	0.0575*	0.3611*	0.0084*	0.0644*	0.2263*	0.0660*	0.0448*	0.1289*	-0.0006	1

4.6.2. Logit Regression Analysis

In order to investigate further the relative importance of the factors affecting the debt-free decisions, I carry out the multivariate logit regressions reported in table 4.12, where the dependant variable takes the value of zero if the SME uses debt in a given year and one for a debt-free SME if it has neither current nor long –term debt in a given year:

$$\Pr\,(Y_{i,t} = 1) = \frac{1}{1 + e^{\alpha + \beta X_{i,t}}} \qquad (4)$$

Where (i) indicates the SME firm, (t) the time, and X is a vector of independent variables that includes: Cash (cash and marketable securities), Size (Log of total assets), TA (tangible assets), CI (capital intensity ratio), FCF (Free cash flow), DR (Dividend Ratio), RD (research and development ratio), AD (advertising expenses), AGE (Log of the SME's age), CRATING (credit rating dummy), OL5 (5 years operating leases), NDTS (non-debt tax shields), NPL (net pension liabilities), AS (Assets Sale), CETA (Capital Expenditure ratio), ABCE (Abnormal capital expenditure). Extreme outliers in this study have been eliminated so that my models are not heavily influenced by them: I have winsorised all my independent variables between the 5^{th} and 95^{th} percentiles.

The second column from each regression panel further provides the marginal probability value for each independent variable. This reported value helps in assessing the effects on probability of changing a predictor from one level to another. It is estimated by providing the change in probability corresponding to one standard deviation change around the mean for each independent variable (or for the change from zero to one for a dummy variable). In order to address any potential concerns about the model specification, I use the method of White (1980) to correct for the standard errors for cross-sectional heteroskedasticity and cluster all the standard errors at the SME level.

Four regression models are estimated where the first one reports the regression results for the whole SMEs sample, while the second, third and fourth reports the regression results for micro, small, and medium samples respectively.

Table 4.12 shows that, controlling for other variables, a one standard deviation increase in cash is associated with an increase in the propensity to become a debt-free firm of 28.2% for the SMEs sample, whereas this probability increases to reach 31.5% for micro SMEs. The results also show that the probability of being classified as debt-free relative to debt is greater for SMEs with higher free cash flows, R&D expenses, and dividend payments. On the other hand, a one standard deviation increase in the SMEs size decreases the propensity to become debt-free SME by 1.65% for the whole sample and 1.89% for micro SMEs, whereas the results are insignificant for small and medium firms. Moreover, micro, small, and medium SMEs that have a greater age are more likely to become debt-free SMEs during their life. Controlling for other firm characteristics, an increase from one-half standard deviation below to one-half standard deviation above the mean of asset sales and capital expenditure increases the probability of SMEs, across their different size segments, becoming debt-free. This may indicate that SMEs sell their assets to finance capital expenditure. The credit rating of an SME is also highly significant and negative, except for small SMEs which indicates that the existence of long-term credit rating decreases the probability of a SME becoming debt-free SME. Finally, the coefficient estimates of OL5, NPL, and NTDS indicate significantly negative relationships with the debt-free likelihood which contradict the findings of my univariate analysis.

Table 4.12 logit regressions to test the determinants of debt-free policy
This table reports the results of logit regressions on the sample over 1980-2014. The dependant variable is the dummy that equals one if the firm-year is debt-free and zero otherwise. The second column from each regression panel provides the marginal probability value for each independent variable. Coefficients t-statistics are reported in parentheses under the coefficient values. Both year and industry effects are controlled for in the regressions. All standard errors adjusted for heteroskedasticity and clustering at the firm level. Coefficients marked with ***, **, * are significant at the 1%, 5%, and 10% level, respectively.

	SMEs		Micro		Small		Medium	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model 1	Marginal Pro.	Model 2	Marginal Pro.	Model 3	Marginal Pro.	Model 4	Marginal Pro.
Cash	2.225***	0.282***	2.035***	0.315***	2.099***	0.263***	2.583***	0.245***
	(0.0660)	(0.00950)	(0.0817)	(0.0138)	(0.121)	(0.0169)	(0.143)	(0.0168)
Size	-0.130***	-0.0165***	-0.122***	-0.0189***	0.0722	0.00903	0.0212	0.00201
	(0.0119)	(0.00153)	(0.0153)	(0.00242)	(0.0325)	(0.00408)	(0.0349)	(0.00331)
FCF	0.738***	0.0934***	0.631***	0.0979***	0.586***	0.0733***	1.863***	0.177***
	(0.0428)	(0.00560)	(0.0481)	(0.00762)	(0.0802)	(0.0103)	(0.152)	(0.0152)
CI	-0.0172	-0.00217	-0.130***	-0.0201***	0.0478	0.00598	0.0145	0.00137
	(0.0225)	(0.00285)	(0.0308)	(0.00472)	(0.0706)	(0.00880)	(0.129)	(0.0123)
RD	1.087***	0.138***	0.683***	0.106***	0.955***	0.120***	1.888***	0.179***
	(0.129)	(0.0164)	(0.168)	(0.0261)	(0.229)	(0.0289)	(0.264)	(0.0257)
DR	0.888***	0.112***	0.322	0.0499	0.471	0.0589	3.591***	0.341***
	(0.289)	(0.0368)	(0.365)	(0.0566)	(0.483)	(0.0605)	(0.639)	(0.0632)
TA	-2.710***	-0.343***	-1.629***	-0.252***	-3.661***	-0.458***	-3.785***	-0.359***
	(0.160)	(0.0187)	(0.164)	(0.0248)	(0.330)	(0.0362)	(0.430)	(0.0343)
AGE	0.112***	0.0142***	0.104***	0.0161***	0.182***	0.0228***	0.261***	0.0248***
	(0.0215)	(0.00276)	(0.0268)	(0.00421)	(0.0411)	(0.00524)	(0.0469)	(0.00461)
AS	3.318***	0.420***	1.008**	0.156**	1.584***	0.198***	4.816***	0.457***
	(0.331)	(0.0422)	(0.494)	(0.0764)	(0.591)	(0.0741)	(0.531)	(0.0522)
CETA	1.168***	0.148***	0.764***	0.118***	1.555***	0.195***	1.934***	0.183***
	(0.243)	(0.0303)	(0.257)	(0.0396)	(0.517)	(0.0631)	(0.662)	(0.0600)
ABCE	-0.391***	-0.0495***	-0.540***	-0.0837***	0.0857	0.0107	-0.186	-0.0176
	(0.101)	(0.0128)	(0.156)	(0.0241)	(0.178)	(0.0223)	(0.187)	(0.0177)
CRATING	-1.228***	-0.155***	-1.385***	-0.215***	-0.600	-0.0750	-1.299***	-0.123***
	(0.231)	(0.0292)	(0.427)	(0.0660)	(0.495)	(0.0620)	(0.319)	(0.0304)
OL5	-1.100***	-0.139***	-1.119***	-0.173***	-0.751***	-0.0940***	-0.673**	-0.0638**
	(0.129)	(0.0165)	(0.159)	(0.0246)	(0.224)	(0.0283)	(0.263)	(0.0252)
NPL	-2.646**	-0.335**	-3.524*	-0.546*	-0.416	-0.0521	-2.750*	-0.261*
	(1.057)	(0.134)	(1.823)	(0.283)	(1.327)	(0.166)	(1.469)	(0.139)
NDTS	-1.271***	-0.161***	-1.382***	-0.214***	-0.798	-0.0999	0.0130	0.00124
	(0.285)	(0.0361)	(0.302)	(0.0467)	(0.605)	(0.0758)	(0.674)	(0.0639)
Constant	-1.647***		-1.135***		-1.702***		-2.707***	
	(0.335)		(0 .389)		(0.478)		(0.669)	
Pseudo R^2	0.1404		0.1476		0.141		0.1598	
Obs.	91,015	91,015	28,328	28,328	25,964	25,964	36,419	36,419

4.6.3. Entry and Exit Decisions

I extend the above regressions to examine the determinants that cause an SME to switch from being debt-free to taking on debt and vice versa. Two dependant variables have been constructed for two regression models. An entry (exit) event is defined as an SME following a debt (debt-free) policy in the last year and a debt-free (debt) policy in the current year. The observations used in the two regression models, namely entry and exit regressions are the same observations used for the whole logit regression model reported in table 4.12. The reason behind this is that the same firm-year observations used in the whole regression are used in the entry and exit regression models and the only difference is the way in which the dependant variable has been defined. For example, the dependant variable in the entry model takes the value of 1 at time t if the firm-year observation is debt in time t-1 and becomes debt-free in time t. Therefore, no observations are lost; it simply depends on the way the dependant variable is defined.

Tables 4.13 and 4.14 provide us with important information about the determinants that cause SMEs to switch from debt to debt-free (entry decision). SMEs that are more profitable with greater cash, more R&D expenses, and greater dividend payments are more likely to become debt-free. Smaller and younger SMEs with less capital intensity and tangible assets are more likely to become debt-free. In addition, OL5 and NPL do not seem to play a significant role in affecting the probability of becoming debt-free, whereas, in line with my hypothesis and not in accordance with the finding in table 4.9, an increase in NDTS significantly increases the probability of SMEs becoming debt-free. An increase in asset sales and capital expenditure, and a decrease in abnormal capital expenditure lead SMEs to switch to become debt-free.

On the other hand, most of the variables for the exit decision have the opposite sign compared to the entry decision, with a few exceptions such as capital intensity (CI), R&D expenses (RD), tangible assets (TA), and the age of the SMEs. Moreover, SMEs with higher free cash flows are less likely to become debt SMEs. Larger dividend payments and higher non-debt tax shields are negatively related to exit decisions. Finally, debt-free SMEs are less likely to take on leverage when they have higher abnormal capital expenditure which reflects the importance of future financial flexibility in debt-free policy decisions.

Table 4.13 entry decision

This table reports the results of logit regressions on entry decisions of the debt-free SMEs. An entry decision is defined as SME being non-debt in the last year and debt-free in the current year. The dependant variable is the dummy that equals one if the firm-year is debt-free and zero otherwise. The second column from each regression panel provides the marginal probability value for each independent variable. Coefficients t-statistics are reported in parentheses under the coefficient values. Both year and industry effects are controlled for in the regressions. All standard errors adjusted for heteroskedasticity and clustering at the firm level. Coefficients marked with ***, **, * are significant at the 1%, 5%, and 10% level, respectively.

	SMEs		Micro		Small		Medium	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model 1	Marginal Pro.	Model 2	Marginal Pro.	Model 3	Marginal Pro.	Model 4	Marginal Pro.
Cash	1.033***	0.0748***	0.751***	0.0635***	1.223***	0.0889***	1.440***	0.0826***
	(0.0603)	(0.00442)	(0.0825)	(0.00698)	(0.111)	(0.00830)	(0.130)	(0.00777)
Size	-0.0668***	-0.00484***	-0.0565***	-0.00478***	-0.0407	-0.00296	-0.0338	-0.00194
	(0.0101)	(0.000741)	(0.0145)	(0.00123)	(0.0297)	(0.00216)	(0.0298)	(0.00171)
FCF	0.384***	0.0278***	0.262***	0.0221***	0.324***	0.0236***	1.200***	0.0688***
	(0.0400)	(0.00290)	(0.0494)	(0.00417)	(0.0731)	(0.00535)	(0.143)	(0.00828)
CI	-0.0382	-0.00277	-0.127***	-0.0107***	0.104	0.00760	0.0742	0.00426
	(0.0241)	(0.00175)	(0.0337)	(0.00281)	(0.0719)	(0.00521)	(0.113)	(0.00651)
RD	0.743***	0.0538***	0.540***	0.0457***	0.439**	0.0319**	1.325***	0.0760***
	(0.112)	(0.00811)	(0.168)	(0.0142)	(0.189)	(0.0138)	(0.228)	(0.0132)
DR	0.752***	0.0545***	0.290	0.0246	0.730	0.0531	2.197***	0.126***
	(0.261)	(0.0189)	(0.367)	(0.0310)	(0.478)	(0.0348)	(0.560)	(0.0325)
TA	-1.866***	-0.135***	-0.937***	-0.0792***	-2.582***	-0.188***	-3.051***	-0.175***
	(0.125)	(0.00862)	(0.137)	(0.0115)	(0.270)	(0.0180)	(0.317)	(0.0163)
AGE	-0.0557***	-0.00404***	0.0451*	0.00381*	-0.0850**	-0.00618**	-0.119***	-0.00680***
	(0.0185)	(0.00134)	(0.0257)	(0.00217)	(0.0371)	(0.00269)	(0.0364)	(0.00208)
AS	2.180***	0.158***	2.291***	0.194***	1.267**	0.0921**	1.861***	0.107***
	(0.311)	(0.0226)	(0.490)	(0.0414)	(0.611)	(0.0445)	(0.512)	(0.0295)
CETA	0.863***	0.0625***	0.640**	0.0541**	1.165***	0.0848***	1.238**	0.0710**
	(0.228)	(0.0164)	(0.279)	(0.0235)	(0.433)	(0.0311)	(0.585)	(0.0330)
ABCE	-0.185	-0.0134	-0.198	-0.0168	-0.195	-0.0142	-0.000219	-1.26e-05
	(0.119)	(0.00861)	(0.192)	(0.0162)	(0.201)	(0.0146)	(0.217)	(0.0124)
CRATING	-0.795***	-0.0576***	-1.257*	-0.106*	-0.323	-0.0235	-0.633**	-0.0363**
	(0.234)	(0.0169)	(0.650)	(0.0547)	(0.570)	(0.0414)	(0.277)	(0.0158)
OL5	-0.0701	-0.00508	-0.148	-0.0125	-0.0183	-0.00133	0.107	0.00614
	(0.0972)	(0.00704)	(0.132)	(0.0112)	(0.191)	(0.0139)	(0.199)	(0.0114)
NPL	-1.620*	-0.117*	-2.190	-0.185	0.397	0.0289	-0.854	-0.0490
	(0.832)	(0.0602)	(2.104)	(0.178)	(1.658)	(0.121)	(0.990)	(0.0568)
NDTS	1.058***	0.0766***	0.653**	0.0552**	1.333***	0.0970***	1.721***	0.0987***
	(0.221)	(0.0160)	(0.273)	(0.0230)	(0.414)	(0.0301)	(0.523)	(0.0301)
Constant	-3.409***		-3.386***		-3.453***		-3.632***	
	(0.299)		(0.391)		(0.492)		(0.684)	
Pseudo R^2	0.0486		0.0394		0.054		0.0736	
Obs.	91,015	91,015	28,328	28,328	25,964	25,964	36,419	36,419

Table 4.14 exit decision
This table reports the results of logit regressions on exit decisions of the debt-free SMEs. An exit decision is defined as SME being debt in the last year and debt-free in the current year. The dependant variable is the dummy that equals one if the firm-year is debt-free and zero otherwise. The second column from each regression panel provides the marginal probability value for each independent variable. Coefficients t-statistics are reported in parentheses under the coefficient values. Both year and industry effects are controlled for in the regressions. All standard errors adjusted for heteroskedasticity and clustering at the firm level. Coefficients marked with ***, **, * are significant at the 1%, 5%, and 10% level, respectively.

	SME		Micro		Small		Medium	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Model 2	Marginal Pro.	Model 2	Marginal Pro.	Model 2	Marginal Pro.	Model 2	Marginal Pro.
Cash	0.569***	0.0399***	0.574***	0.0497***	0.564***	0.0422***	0.412***	0.0210***
	(0.0632)	(0.00444)	(0.0827)	(0.00713)	(0.120)	(0.00906)	(0.150)	(0.00767)
Size	0.0955***	0.00670***	0.0871***	0.00753***	0.00586	0.000438	0.0662**	0.00337**
	(0.0102)	(0.000713)	(0.0142)	(0.00123)	(0.0292)	(0.00218)	(0.0325)	(0.00165)
FCF	-0.0910**	-0.00637**	-0.0989**	-0.00855**	-0.250***	-0.0187***	-0.0130	-0.000662
	(0.0356)	(0.00249)	(0.0441)	(0.00382)	(0.0659)	(0.00490)	(0.112)	(0.00568)
CI	-0.0471**	-0.00330**	-0.139***	-0.0121***	0.0363	0.00271	0.124	0.00632
	(0.0235)	(0.00164)	(0.0319)	(0.00271)	(0.0738)	(0.00552)	(0.0850)	(0.00432)
RDR	0.416***	0.0291***	-0.0372	-0.00322	0.238	0.0178	0.965***	0.0491***
	(0.119)	(0.00829)	(0.166)	(0.0144)	(0.209)	(0.0156)	(0.257)	(0.0131)
DR	-0.432	-0.0303	-0.948**	-0.0820**	-0.0972	-0.00727	-0.61	-0.031
	(0.300)	(0.0210)	(0.437)	(0.0378)	(0.459)	(0.0344)	(0.655)	(0.0334)
TA	-1.300***	-0.0911***	-0.473***	-0.0409***	-2.149***	-0.161***	-2.382***	-0.121***
	(0.110)	(0.00763)	(0.128)	(0.0111)	(0.222)	(0.0158)	(0.287)	(0.0138)
LAGE	-0.0191	-0.00134	0.0125	0.00108	-0.00967	-0.000723	-0.00833	-0.000424
	(0.0189)	(0.00132)	(0.0253)	(0.00219)	(0.0365)	(0.00273)	(0.0401)	(0.00204)
AS	-0.0743	-0.00521	-0.013	-0.00113	-0.814	-0.0609	-0.530	-0.0270
	(0.356)	(0.0250)	(0.544)	(0.0470)	(0.665)	(0.0497)	(0.628)	(0.0320)
CETA	2.147***	0.151***	1.758***	0.152***	2.680***	0.201***	3.098***	0.158***
	(0.185)	(0.0129)	(0.241)	(0.0207)	(0.360)	(0.0263)	(0.453)	(0.0223)
ABCE	0.281**	0.0197**	0.0202	0.00175	0.663***	0.0496***	0.300	0.0153
	(0.116)	(0.00813)	(0.189)	(0.0163)	(0.193)	(0.0145)	(0.216)	(0.0110)
CRATING	0.701***	0.0491***	0.668	0.0578	0.245	0.0183	0.837**	0.0426**
	(0.251)	(0.0176)	(0.549)	(0.0473)	(0.517)	(0.0387)	(0.362)	(0.0183)
OL5	-0.267***	-0.0187***	-0.491***	-0.0424***	-0.134	-0.00999	0.165	0.00839
	(0.0966)	(0.00677)	(0.141)	(0.0121)	(0.174)	(0.0130)	(0.205)	(0.0104)
PNL	-1.606*	-0.113*	0.663	0.0573	2.080*	0.156*	-2.796**	-0.142**
	(0.930)	(0.0651)	(1.892)	(0.164)	(1.243)	(0.0927)	(1.335)	(0.0678)
NDTS	-1.440***	-0.101***	-1.427***	-0.123***	-1.247**	-0.0933**	-1.226*	-0.0624*
	(0.254)	(0.0177)	(0.302)	(0.0260)	(0.512)	(0.0381)	(0.647)	(0.0329)
Constant	-2.830***		-2.654***		-2.354***		-5.057***	
	(0.282)		(0.386)		(0.465)		(1.063)	
Pseudo R^2	0.0417		0.0439		0.038		0.0449	
Obs.	91,015	91,015	28,328	28,328	25,964	25,964	36,419	36,419

4.7. Robustness Tests

This section provides further tests to address any potential concerns about the model specification and estimation problems. The first concern that might arise is the endogeneity problem as leverage decisions are endogenous to other financial and investment decisions (Strebulaev and Yang, 2013). To tackle the endogeneity problem I re-estimate the two models using one year lagged variables. From table 4.15 I can conclude that the results are qualitatively similar to those found in table 4.12. Moreover, in line with the assertion of Graham (2000) that large, liquid firms facing low ex-ante costs of distress are undervalued, Strebulaev and Yang (2013) argue that debt-free firms are profitable, accumulate larger cash balances, and pay out larger dividends hence they violate the standard trade-off proposition by taking Graham's (2000) assertion to the extreme. Secondly, I check for heteroskedasticity by using the method of White (1980) to correct for the standard errors for cross-sectional heteroskedasticity and cluster all the standard errors at the SME level. Thirdly I run probit regressions as alternative to logit regressions and the results reported in table 4.16 are similar to those estimated using logit regressions.

Table 4.15 logit regressions with lagged independent variables
This table reports the results of logit regressions on the sample over 1980-2014 with lagged independent variables to adjust for endogeneity problem that might exist. The dependant variable is the dummy that equals one if the firm-year is debt-free and zero otherwise. The second column from each regression panel provides the marginal probability value for each independent variable. Coefficients't-statistics are reported in parentheses under the coefficient values. Both year and industry effects are controlled for in the regressions. All standard errors adjusted for heteroskedasticity and clustering at the firm level. Coefficients marked with ***, **, * are significant at the 1%, 5%, and 10% level, respectively.

	SMEs		Micro		Small		Medium	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model 2	Marginal Pro.	Model 2	Marginal Pro.	Model 2	Marginal Pro.	Model 2	Marginal Pro.
Cash	1.040***	0.0739***	0.953***	0.0908***	1.092***	0.0802***	1.254***	0.0639***
	(0.0655)	(0.00475)	(0.0917)	(0.00886)	(0.113)	(0.00855)	(0.138)	(0.00730)
Size	-0.172***	-0.0122***	-0.153***	-0.0146***	-0.192***	-0.0141***	-0.228***	-0.0116***
	(0.0109)	(0.000780)	(0.0156)	(0.00149)	(0.0257)	(0.00189)	(0.0288)	(0.00146)
FCF	0.193***	0.0137***	0.165***	0.0158***	-0.00657	-0.000483	0.359***	0.0183***
	(0.0394)	(0.00281)	(0.0516)	(0.00493)	(0.0669)	(0.00491)	(0.111)	(0.00569)
CI	2.07e-05	1.47e-06	-4.96e-05	-4.73e-06	0.000108***	7.95e-06***	8.41e-05***	4.29e-06***
	(1.68e-05)	(1.19e-06)	(3.21e-05)	(3.03e-06)	(3.32e-05)	(2.43e-06)	(2.78e-05)	(1.40e-06)
RDR	0.488***	0.0347***	0.0413	0.00394	0.402**	0.0296**	0.769***	0.0392***
	(0.124)	(0.00880)	(0.187)	(0.0178)	(0.204)	(0.0149)	(0.250)	(0.0128)
DR	0.0797	0.00566	-0.673	-0.0642	0.482	0.0354	0.776	0.0396
	(0.293)	(0.0208)	(0.495)	(0.0472)	(0.462)	(0.0339)	(0.547)	(0.0280)
TA	-1.818***	-0.129***	-0.876***	-0.0836***	-2.811***	-0.206***	-3.305***	-0.169***
	(0.133)	(0.00904)	(0.142)	(0.0135)	(0.269)	(0.0180)	(0.364)	(0.0164)
AGE	-0.163***	-0.0116***	-0.240***	-0.0228***	-0.0924***	-0.00678***	-0.0714*	-0.00364*
	(0.0198)	(0.00139)	(0.0296)	(0.00275)	(0.0349)	(0.00256)	(0.0368)	(0.00187)
AS	1.343***	0.0953***	0.937	0.0894	1.497**	0.110**	0.872	0.0445
	(0.365)	(0.0259)	(0.579)	(0.0551)	(0.653)	(0.0479)	(0.613)	(0.0313)
CETA	1.641***	0.117***	1.266***	0.121***	1.996***	0.147***	2.657***	0.135***
	(0.217)	(0.0152)	(0.283)	(0.0267)	(0.418)	(0.0301)	(0.540)	(0.0265)
ABCE	-0.425***	-0.0301***	-0.382*	-0.0364*	-0.467**	-0.0343**	-0.483**	-0.0246**
	(0.127)	(0.00902)	(0.214)	(0.0204)	(0.210)	(0.0155)	(0.232)	(0.0119)
CRATING	-0.768**	-0.0545**	-1.038	-0.0990	0.0141	0.00103	-0.804**	-0.0410**
	(0.317)	(0.0224)	(0.758)	(0.0720)	(0.554)	(0.0407)	(0.395)	(0.0200)
OL5	-0.389***	-0.0276***	-0.559***	-0.0533***	-0.470**	-0.0345**	-0.132	-0.00671
	(0.111)	(0.00790)	(0.171)	(0.0162)	(0.186)	(0.0137)	(0.220)	(0.0112)
PNL	-0.516	-0.0367	2.769	0.264	1.814	0.133	-2.324	-0.119
	(0.968)	(0.0687)	(1.861)	(0.177)	(1.393)	(0.102)	(1.450)	(0.0739)
NDTS	-0.617**	-0.0438**	-0.885***	-0.0844***	-0.309	-0.0227	0.0114	0.000583
	(0.269)	(0.0190)	(0.319)	(0.0303)	(0.560)	(0.0411)	(0.644)	(0.0328)
Constant	-2.829***		-2.023***		-3.190***		-2.212***	
	(0.404)		(0.390)		(0.842)		(0.719)	
Pesudo R^2	0.061		0.0607		0.0583		0.0629	
Obs.	77,789	77,789	20,566	20,566	23,668	23,668	33,175	33,175

Table 4.16 probit regressions to test the determinants of debt-free policy

This table reports the results of probit regressions on the sample over 1980-2014. The dependant variable is the dummy that equals one if the firm-year is debt-free and zero otherwise. The second column from each regression panel provides the marginal probability value for each independent variable. Coefficients't-statistics are reported in parentheses under the coefficient values. Both year and industry effects are controlled for in the regressions. All standard errors adjusted for heteroskedasticity and clustering at the firm level. Coefficients marked with ***, **, * are significant at the 1%, 5%, and 10% level, respectively.

	SMEs		Micro		Small		Medium	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Model 2	Marginal Pro.	Model 2	Marginal Pro.	Model 2	Marginal Pro.	Model 2	Marginal Pro.
Cash	1.342***	0.321***	1.229***	0.344***	1.273***	0.303***	1.546***	0.298***
	(0.0381)	(0.00996)	(0.0476)	(0.0141)	(0.0700)	(0.0179)	(0.0820)	(0.0180)
Size	-0.0771***	-0.0184***	-0.0742***	-0.0208***	0.0451**	0.0107**	0.0107	0.00205
	(0.00666)	(0.00161)	(0.00868)	(0.00246)	(0.0181)	(0.00432)	(0.0191)	(0.00369)
FCFR	0.399***	0.0955***	0.353***	0.0990***	0.310***	0.0738***	0.949***	0.183***
	(0.0235)	(0.00576)	(0.0270)	(0.00770)	(0.0437)	(0.0106)	(0.0793)	(0.0158)
CI	-0.00680	-0.00163	-0.0585***	-0.0164***	0.0118	0.00281	0.0160	0.00309
	(0.0117)	(0.00279)	(0.0147)	(0.00410)	(0.0375)	(0.00891)	(0.0545)	(0.0105)
RDR	0.632***	0.151***	0.402***	0.112***	0.563***	0.134***	1.073***	0.207***
	(0.0734)	(0.0176)	(0.0962)	(0.0270)	(0.130)	(0.0310)	(0.150)	(0.0292)
DR	0.523***	0.125***	0.148	0.0413	0.278	0.0660	2.150***	0.415***
	(0.167)	(0.0401)	(0.212)	(0.0593)	(0.282)	(0.0671)	(0.359)	(0.0713)
TA	-1.346***	-0.322***	-0.880***	-0.246***	-1.813***	-0.431***	-1.758***	-0.339***
	(0.0791)	(0.0182)	(0.0858)	(0.0237)	(0.165)	(0.0366)	(0.200)	(0.0352)
LAGE	0.0555***	0.0133***	0.0552***	0.0155***	0.0920***	0.0219***	0.131***	0.0253***
	(0.0119)	(0.00289)	(0.0152)	(0.00432)	(0.0228)	(0.00552)	(0.0250)	(0.00496)
AS	1.883***	0.451***	0.569**	0.159**	0.912***	0.217***	2.709***	0.523***
	(0.189)	(0.0455)	(0.280)	(0.0784)	(0.335)	(0.0798)	(0.306)	(0.0600)
CETA	0.554***	0.133***	0.412***	0.115***	0.699***	0.166***	0.785**	0.151**
	(0.126)	(0.0299)	(0.140)	(0.0391)	(0.262)	(0.0614)	(0.334)	(0.0631)
ABCE	-0.234***	-0.0559***	-0.315***	-0.0883***	0.0399	0.00950	-0.104	-0.0201
	(0.0561)	(0.0134)	(0.0884)	(0.0247)	(0.0987)	(0.0235)	(0.102)	(0.0197)
CRATING	-0.577***	-0.138***	-0.659***	-0.185***	-0.246	-0.0585	-0.609***	-0.118***
	(0.108)	(0.0258)	(0.203)	(0.0567)	(0.259)	(0.0616)	(0.146)	(0.0284)
OL5	-0.580***	-0.139***	-0.587***	-0.164***	-0.401***	-0.0954***	-0.337***	-0.0650***
	(0.0656)	(0.0158)	(0.0834)	(0.0233)	(0.117)	(0.0281)	(0.129)	(0.0252)
PNL	-1.419***	-0.339***	-2.058**	-0.576**	-0.240	-0.0570	-1.402*	-0.270*
	(0.549)	(0.131)	(0.976)	(0.273)	(0.742)	(0.176)	(0.739)	(0.142)
NDTS	-0.620***	-0.148***	-0.703***	-0.197***	-0.390	-0.0928	0.0639	0.0123
	(0.147)	(0.0352)	(0.158)	(0.0443)	(0.310)	(0.0740)	(0.362)	(0.0699)
Constant	-1.015***		-0.698***		-1.060***		-1.631***	
	(0.188)		(0.233)		(0.263)		(0.358)	
Pesudo R^2	0.1394		0.1466		0.1403		0.1579	
Obs.	91,015	91,015	28,328	28,328	25,964	25,964	36,419	36,419

Table 4.17 definition of variables

Code	Variable	Definition	Compustat item code
		Financing Constraints	
Cash	Cash Holdings	Cash and marketable securities / total assets	Cash = (CH+MSA)/AT
TA	Tangible Assets	Tangible Assets / total assets	TA = PPENT/AT
CI	Capital Intensity	Fixed Assets / Number of Employees	CI = PPENT/(EMP*1000)
CRATING	Credit Rating Dummy	equals (1) if SME has long-term credit rating and (0) otherwise	SPLTICRM
IG	Investment Grade	equals (1) if SME has an investment-grade rating (BBB- or higher), zero for rating (BB+ or lower), and missing otherwise	
KZ	KZ Index (Based on Baker et al. (2003)	$KZ = \left(\frac{1.002\ CF_t}{AT_{t-1}}\right) + \left(\frac{39.368\ DIV_t}{AT_{t-1}}\right) + \left(\frac{1.315\ CHE_t}{AT_{t-1}}\right) + 3.139\ LEV_t$	
Cash Flow			CF = DP+IB
cash dividend			DIV = DVP+DVC
leverage ratio			LEV=(DLTT+DLC)/(DLTT+DLC+SEQ)
AGE	SME's Age	Number of years since the SME's record first appears in Compustat	
		Valuation and Financing Activities	
MVTA	Market Value of Total Assets	Total Assets - book value of equity + market value of Equity	MVTA =AT-CEQ+(PRCC_F*CSHO)
MB	Market to Book Ratio	Market value of Total Assets/Total Assets	MB=MVTA/AT
NDI	Net Debt Issuance	Ratio of the change in current and long-term debt to total assets	(DLCt + DLTTt - DLCt-1 - DLTTt-1)/ATt
NEI	Net Equity Issuance	Ratio of net equity issuance to total assets	(SSTK-PRSTKC)/AT
CME	Change in Market Equity with split adjustment	{(csho t*ajex t)-(csho t-1*ajex t-1)*(prcc_f t/ajex t)+(prcc_f t-1/ajex t-1)}/2	
		Profitability	
OCF	Operating Cash Flow	Operating income before depreciation / Total Assets	OCF = OIBDP/AT
FCF	Free Cash Flow	I follow Frank and Goyal (2003) definition:	
	1	For SMEs reporting format codes (SCF = 1 to 3): FCF = Income before extra items + Discontinued Operation + Depreciation and Amortization + Deferred Taxes + Equity in Net Loss + Gain/Loss from PPE + Other funds from operations + Other sources of funds	FCF = IBC+XIDOC+DPC+TXDC+ESUBC+SPPIV+FOPO+FSRCO
	2	For SMEs reporting format codes (SCF = 7): FCF = Income before extra items + Discontinued Operation + Depreciation and Amortization + Deferred Taxes + Equity in Net Loss + Gain/Loss from PPE + Other funds from operations + Exchange Rate Effect	FCF = IBC+XIDOC+DPC+TXDC+ESUBC+SPPIV+FOPO+EXRE

NI	Net Investment Ratio	Net Investment / Total Assets	NI = NI/AT
NIFCF	Free Cash Flow Deficit	Net investment Ratio - Free Cash Flow	NIFCF = NIR - FCFR
NIOCF	Operating Cash Flow Deficit	Net Investment Ratio - Operating Cash Flow	NIOCF = NIR - OCF
RD	Ratio of research and development expenses to total assets	Research and Development Expenses/Total Assets	XRD/AT
AD	Ratio of Advertising Expenses to total Assets	Advertising Expenses/Total Assets	PPENT/AT
DR	Dividend Ratio	Dividend/Total Assets	DR=DV/AT
Non-Debt Tax shield, Pensions, and lease commitments			
NDTS	Non-Debt Tax Shield	(Depreciation and Amortization + Deferred Tax and Investment Tax Credit)/ Total Assets	NDTS = (DP+TXDITC)/AT
OL5	Five Years Operating Lease	Five Years Lease Commitments / Total Assets	OL5=MRCT/AT
OL1	One Year Operating Lease	One Year Lease Commitments / Total Assets	OL1=MRC1/AT
PO	Pension Obligations	Projected Pension Obligations + Project Pension Obligations (Underfunded)	PO=PBPRO+PBPRU
PA	Pension Assets	Pension Plan Assets + Pension Plan Assets (Underfunded)	PA=PPLAO+PPLAU
NPL	Net Pension Liabilities	Pension Obligations - Pension Assets, if Pension obligations are greater than or equal to Pension Assets, and as zero otherwise	max(PO-PA,0)
Low-leverage Puzzle			
MLR	Market Leverage Ratio	Total Debt/Market Value of Total Assets	MLR=(DLC+DLTT)/MVTA
BLR	Book Leverage Ratio	(long term debt + short term debt)/ Total Assets	(DLC + DLTT)/AT
Future Investments			
ABCE	Abnormal Capital Expenditure	Definition according to titman et al. (2004)	(CEt/(CEt-1 + CEt-2 + CEt-3)/3) -1
CETA	Capital Expenditure Ratio	Capital Expenditure/Total Assets	CAPX/AT
AS	Asset Sale Ratio	(Sale of Property + Sale of Investments)/Total Assets	AS=(SPPE+SIV)/AT

4.8. Conclusion

This paper investigates the determinants of the puzzling zero-leverage behaviour among US SMEs. In addition, I try to capture any differences that may exist among different SMEs size categories and to what extent size affects the zero-leverage behaviour. To answer this question I first classify SMEs into three size categories (micro, small, and medium) depending on the number of employees and average annual receipts.

My empirical analysis was performed using panel data available from the Compustat database. The sample employs annual firm-level accounting data for (14,093) US small and medium-sized enterprises having fewer than 500 employees and average annual receipts of less than $ 7.5 million, covering an analysis period from 1980 to 2014. After filtering the data, there were 95,450 firm-year observations of which 32,244 were for micro SMEs, 26,230 for small SMEs, and 36,669 for medium SMEs. These observations include 18,764 debt-free observations for the whole SMEs sample, 8,135 for micro SMEs, 5,028 for small SMEs, and 5,577 for medium SMEs. On average 20% of the total sample observations are debt-free, the micro sample has the highest level of debt-free observations, followed by small, then medium, with averages of 25%, 19%, and 15% respectively. My findings indicate that borrowing constraints and financing activities play a significant role in the debt-free capital structure decisions of the SME companies. Debt-free SMEs have significantly less tangible assets, lower capital intensity ratios, and lower KZ index scores which indicate their higher constraints on borrowing. Moreover, SMEs tend to build up a good reputation in order to facilitate their dependence on the external equity market for financing, where they have higher MB ratio and net equity issuance. On the other hand, SMEs' reliance on equity market financing could also be due to their low credit ratings which means they are unable to issue debt at favourable conditions.

A surprising result is that a large number of debt-free SMEs pay significantly higher dividends than their debt SMEs counterparts. This might be due to the fact that dividend payments address shareholders' concerns about the agency problems especially for large profitable debt-free SMEs, with dividends being used as a debt substitute to tackle the agency problem of high free cash flow. Furthermore, higher dividend payments can be seen as a way to enhance the ability of these highly debt-constrained SMEs to raise equity capital on more favourable terms without excessive adverse effects.

In addition, I find that pension obligations and lease commitments do not play a significant role in explaining the debt-free policy. However, when conducting the logit regressions on entry and exit decisions of the debt-free SMEs I find that the NDTS plays a significant role in explaining the firm's decision whether to enter or exit the debt-free status. Therefore I conclude that if NDTS increases the probability of becoming debt-free (debt) firm increase (decrease).

Chapter Five

5. The Effect of Debt-Free Decisions on SMEs' Failure Probabilities: Evidence from the US Market

5.1. Introduction

Since the seminal work of Modigliani and Miller in 1958, two predominant theories of capital structure namely the "Optimal Trade-off" and "Pecking order" hypotheses have tried to explain the choice between debt and equity financing and the existence of an optimal level of the debt-equity ratio that should be held in the firm. The static version of the trade-off theory suggests that the optimal capital structure involves balancing the corporate tax advantages of debt financing against the costs of financial distress that arise from bankruptcy risks (Kraus and Litzenberger, 1973; Morellec, 2004) and agency costs (Jensen and Meckling, 1976). Any firm that deviates from this optimum is penalized through lower risk-adjusted returns, and potentially failure or acquisition (Chung et al., 2013). The pure version of the pecking order theory is based on informational asymmetry, suggesting that firms do not have leverage targets. They use debt only when retained earnings are insufficient and raise external equity capital only as a last resort (Myers and Majluf, 1984) .

The development of these two theories resulted in several hybrid hypotheses. For example, Fischer et al. (1989) suggest the dynamic capital structure hypothesis which is derived from trade-off theory. They suggest that firms deviate from their optimal capital structure due to economies of scale. However, firms return to their targets using debt financing. On the other hand, Myers (1984) proposes a modified version of the pecking order theory. His hypothesis implies that firms cannot strictly adhere to the pecking order predictions since they face debt capacity limitations and frictions associated with raising capital. A recent study by DeAngelo and DeAngelo (2007) shows that these two main hypotheses are not mutually exclusive and firms might have capital targets with the trade-off theory, but they may depart from the targets by issuing debt to pursue favourable investment opportunities in line with the pecking order theory.

Both theories advocate the use of debt because of either tax benefits or lower costs of asymmetric information. However, neither the trade-off theory nor the pecking order theory is able to explain why so many firms across countries follow a debt-free policy. This extreme debt puzzle refers to the idea that certain firms prefer to have no leverage, contrary to what would maximize their value from a static trade-off theory or pecking order theory point of view. With an increased number of firms tending to have zero-leverage[21], a growing body of literature tries to solve this debt-free puzzle and find the main determinants behind this choice of extreme capital structure (see for example (El kalak and Hudson, 2015b; Strebulaev and Yang, 2013; Bessler et al., 2013; Byoun and Xu, 2013)).

Small and medium-sized enterprises (SMEs) are viewed as the backbone of the economy of many countries all over the world since they are the incubators of employment, growth, and innovation (Altman and Sabato, 2007). SMEs constantly play a vital role in the US economy where statistics from the "US Small Business Administration[22]" show that small businesses made up 99.7% of US employer firms in 2011, and they accounted for 63% of the new jobs created between 1993 and 2013. These numbers emphasize the importance of SMEs as job creation engines. Furthermore, the Bureau of Labour Statistics[23] and a study by the Economist

[21] Bassler et al. (2013) report that one out of every four listed firms in the developed markets abstain from using debt. El Kalak and Hudson (2015b) find that 20% of the US SMEs' sample exhibit zero-debt behaviour, and that this percentage is increasing over their sample period.

[22] The Small Business Administration known as "SBA" was created in 1953 as an independent agency of the federal government to aid, counsel, assist and protect the interests of small businesses in the US. For more details: http://www.sba.gov/

[23] Source: Bureau of Labour Statistics, BED. For the latest employment statistics, see Advocacy's quarterly reports, www.sba.gov/advocacy/10871.

Intelligence Unit in 2009 show that during the financial crisis SMEs continued to hire employees and create new job opportunities (EIU, 2009).

The empirical literature on SMEs has been extensively investigated especially after the Basel Accord for bank capital adequacy (Basel II) (see for example (Saurina and Trucharte, 2004; Altman and Sabato, 2005; Berger, 2006)). These studies covered a broad range of SMEs aspects such as understanding the determinants of capital structure of SMEs (Sogorb-Mira, 2005), investigating the key drivers of SME profitability and riskiness for US banks (Kolari and Shin, 2006) and their lending structure and strategies (Berger and Udell, 2006).

SMEs are usually prone to external financing difficulties compared to large firms (Ardic et al., 2011) which pose more constraints on them in obtaining commercial bank financing, especially long-term loans due to a variety of factors such as lack of collateral, low cash flow, inadequate credit history or high risk (IFC, 2010). Therefore, a substantial volume of research investigates the determinants of the capital structure of SMEs in the US (Berger and Udell, 1998), Europe (Sogorb-Mira, 2005; Ramalho and da Silva, 2009), and Asia (Matlay et al., 2006). Recently, a study conducted by El kalak and Hudson (2015b) explores the zero-debt puzzle of SMEs, providing potential explanations for the choice of zero-debt along various dimensions and examine a number of economic mechanisms that are believed to further explain the phenomenon of extreme debt conservatism in SMEs. They find that borrowing constraints and financing activities play a significant role in the debt-free capital structure decisions of the SMEs. Moreover, they report that a large number of debt-free SMEs pay significantly higher dividends than their debt SMEs counterparts.

Altman et al. (2010) mention that measuring and tracking the failure rate of SMEs is a difficult task due to the difficulties associated with locating and identifying SMEs, in addition to determining the exact reasons for their failure. Despite the existence of these difficulties there is an extensive empirical literature on modelling the default risk of SMEs and investigating the rates and causation of such failures (see for example (Watson and Everett, 1996; Headd, 2003; Carter and Auken, 2006; Altman et al., 2010)). In their paper Altman et al. (2010) mention two principal reasons for SMEs' closure, which are lack of planning and insufficient capitalisation. Hutchinson and Xavier (2006) suggest that financial difficulties are the main factor for SMEs failure, while others such as Peacock (2000) report that poor managerial skills are behind these failures. Carter and Auken (2006) classify default factors into direct and indirect costs. They have suggested that the direct costs such as lack of knowledge, economic climate, and debt financing are the main reasons for SMEs failure, while indirect costs such as self-employment, personal collateral and self-esteem can play a secondary role.

To my knowledge there is no research in the SME literature that explores the main determinants of the failure probabilities of debt-free SMEs. This is an important question, especially as debt-free SMEs deviate substantially from their optimal level of capital structure according to the main theories of capital structure. Hence, they might face lower risk-adjusted returns leading to an increased probability of bankruptcy (Bessler et al., 2013). On the other hand, using no debt in their capital structure might make these SMEs less exposed to leverage risk, which is usually associated with lower failure probabilities (Altman and Sabato, 2007; Altman et al., 2010).

My empirical analysis employs annual firm-level data extracted from the Compustat Database for 95,110 firm-year observations ranging over an analysis period from 1980 to 2013. This sample is divided into two main groups, namely, the debt-SMEs group containing 76,457 firm-year observations and the debt-free-SMEs group, containing 18,653 firm-year observations. Furthermore, within each group I classify SMEs into failed and non-failed SMEs. There are 309 firm-year observations for failed firms within the debt-free group and 622 firm-year observations for failed firms within the debt group. I control for macroeconomic effects by including the change in annual interest rates in the US throughout the sample period.

My methodological framework depends on forecasting bankruptcy probabilities by developing discrete-time duration-dependant hazard models separately for both groups under analysis namely debt and debt-free SMEs. A general overview of my empirical findings shows that different sets of explanatory variables affect the default probabilities of debt and debt-free SMEs. Furthermore, a comparison between the models shows that five explanatory variables: research and development ratio, working capital ratio, tangible assets, abnormal capital expenditure, and asset sales affect the probability of bankruptcy differently for each model, thus suggesting a potential need to treat debt and debt-free SMEs separately when modelling credit risk. Finally, I have provided an out of sample validation following the Shumway (2001) method, my out of sample results show good performance classifications for the both bankruptcy prediction models developed.

The remainder of the chapter is organized as follows:. Section 5.2. outlines the data used in the study, while theoretical discussion and variable selection is presented in section 5.3. Section 5.4. discusses the empirical method that I employ, while section 5.5. provides the empirical findings. Section 5.6. concludes.

5.2. Data

The Compustat database has been used to construct my sample over the period from 1980 to 2013. The sample is limited to all available annual information extracted from Compustat for US SMEs. Small and medium-sized enterprises are defined according to the Small Business Administration (SBA) as having fewer than 500 employees and average annual receipts of less than $7.5 million[24].

[24] For more detailed definition see, El kalak and Hudson (2015a)

Furthermore, in line with other studies, I exclude financial, insurance, and utility SMEs from my sample. These eliminated SMEs have industrial classification (SIC) codes from 6000 to 6999 for financial SMEs and 4900 to 4949 for regulated utilities. In addition, I remove all non-US firms with international standards organization country code of incorporation (FIC) not equal to USA. SMEs are required to have positive values of common equity, total assets, stock price at the end of the fiscal year, and number of shares outstanding. Firm-years with missing data on any of the control variables and dependent variables are deleted.

The final panel data sample employs annual firm-level data for 95,110 firm-year observations. This sample is divided into two main groups namely the debt group containing 76,457 firm-year observations and the debt-free group containing 18,653 firm-year observations. Each SME firm is defined as a debt-free SME if it has neither current nor long–term debt in a given year and a SME firm with any amount of debt in a given year is defined as a debt SME.

Furthermore, within each group I classify SMEs into failed and non-failed SMEs. There are 309 firm-year observations for failed firms within the debt-free group and 622 firm-year observations for failed firms within the debt group. In this study, I consider SMEs to have failed only if they filed for legal bankruptcy proceedings (either Chapter 11 and 7) within the time period studied. SMEs are classified as legally bankrupt in the Compustat database if the company has a "TL" footnote on the status alert (Data item STALT) indicating that the firm is in bankruptcy or liquidation (e.g. Chapter 7/11).

Moreover, I control for macroeconomic effects by including the change in annual interest rates in the US throughout the period of my sample. This macroeconomic variable has been suggested by Hillegeist (2001) as a control for macroeconomic conditions affecting firms' default probabilities. In addition, I control for industry effects by classifying the SMEs into nine distinctive categories according to the SIC codes and including the variable as a factorial variable. Extreme outliers are eliminated so that my models are not heavily influenced by them. I winsorised all my independent variables between the 5th and 95th percentiles. In addition, I have lagged all the covariates by one-time period so that all information is available at the beginning of the relevant time period.

Finally, in order to validate the out-of-sample prediction performance of the models developed, the entire study window is divided into two groups: the estimation period (1980-2008, 28 years) for the model building and the forecasting period (2009-2013, 5 years) for the out-of-sample forecasting performance test.

Table 5.1 reports the frequency of failed and non-failed observations of SMEs for each of the debt and debt-free groups relative to the total number of observations in the sample for each year between 1980 and 2013. A general comparison between panel A and B shows that the percentage of failed SMEs within the debt-free group is much higher than that of the debt group. The SMEs bankruptcy percentage for the debt group is only around 0.811%, whereas it reaches 1.646% for the debt-free group. One possible explanation for this difference is that, if the trade-off theory is correct, SMEs with a debt-free policy deviate substantially from their optimal capital structure, which exposes them to higher probabilities of bankruptcy compared with debt SMEs. This initially suggests that the set of independent variables included in my multivariate models might affect the bankruptcy hazard differently for debt and debt-free SMEs. However, it is also important to notice in panel A, for the debt-free group, that over time the failure percentages of SMEs exhibit a continuous decline from 4.70% in 1980 to just under 0.4% in 2013[25].

[25] This decline in bankruptcy percentage over time is accompanied by a growing preference among SMEs to eschew debt and gradually become debt-free (see e.g. El kalak and Hudson (2015b)).

Table 5.1 number of observations
This table reports the frequency of failed and non-failed firm-year observations of SMEs for each of the debt and debt-free groups relative to the total number of observations in the sample in each year between 1980 and 2013.

	Panel (A)				Panel (B)			
Year	Debt-Free SMEs				Debt SMEs			
	Failed	Non-Failed	Total	%Failed	Failed	Non-Failed	Total	%Failed
1980	11	223	234	4.700855	16	1,875	1,891	0.846113
1981	10	253	263	3.802281	25	1,948	1,973	1.267106
1982	13	286	299	4.347826	37	2,141	2,178	1.698806
1983	6	318	324	1.851852	38	2,297	2,335	1.627409
1984	10	331	341	2.932551	35	2,352	2,387	1.466276
1985	13	346	359	3.62117	33	2,534	2,567	1.285547
1986	11	397	408	2.696078	40	2,686	2,726	1.467351
1987	14	418	432	3.240741	31	2,595	2,626	1.180503
1988	14	426	440	3.181818	29	2,482	2,511	1.154918
1989	11	398	409	2.689487	34	2,420	2,454	1.385493
1990	13	412	425	3.058824	41	2,411	2,452	1.672104
1991	17	438	455	3.736264	30	2,493	2,523	1.189061
1992	13	505	518	2.509653	30	2,540	2,570	1.167315
1993	9	541	550	1.636364	30	2,607	2,637	1.137656
1994	14	583	597	2.345059	11	2,686	2,697	0.407861
1995	13	679	692	1.878613	9	3,114	3,123	0.288184
1996	16	717	733	2.18281	16	3,019	3,035	0.527183
1997	11	696	707	1.55587	12	2,810	2,822	0.42523
1998	7	764	771	0.907912	16	2,953	2,969	0.538902
1999	7	749	756	0.925926	11	2,912	2,923	0.376326
2000	3	767	770	0.38961	12	2,648	2,660	0.451128
2001	9	736	745	1.208054	17	2,527	2,544	0.668239
2002	11	728	739	1.488498	7	2,361	2,368	0.295608
2003	7	704	711	0.984529	12	2,118	2,130	0.56338
2004	8	700	708	1.129944	10	1,899	1,909	0.523834
2005	9	677	686	1.311953	6	1,774	1,780	0.337079
2006	3	636	639	0.469484	9	1,664	1,673	0.537956
2007	5	610	615	0.813008	2	1,564	1,566	0.127714
2008	6	571	577	1.039861	4	1,482	1,486	0.269179
2009	3	548	551	0.544465	7	1,438	1,447	0.48376
2010	3	548	551	0.544465	3	1,341	1,344	0.223214
2011	5	562	562	0.88968	4	1,310	1,314	0.304414
2012	2	551	553	0.361664	3	1,481	1,481	0.202566
2013	2	532	533	0.375235	2	1,354	1,356	0.147493
Total	309	18350	18653	1.65656999	622	75836	76457	0.81352917

5.3. Theoretical Discussion and Variables Selection

In this study, the dependant variable used has a binary outcome where it equals one when the SME files for bankruptcy and zero otherwise. I have developed two different default prediction models named Debt and Debt-Free in order to find the most appropriate set of independent variables which provide the highest significant explanatory power for the probability of failures for debt and debt-free SMEs. Moreover, by applying the failure prediction models I test how each of these covariates influences the failure probabilities of the debt and debt-free groups.

A considerable number of previous studies have empirically tested the existing theories about the debt-free puzzle in particular and capital structure in general in order to find the main determinates of the debt-free puzzle (see among others, (El kalak and Hudson, 2015b; Strebulaev and Yang, 2013; Devos et al., 2012). Since this study focuses on the main determinants of the probability of failure of debt and debt-free SMEs', I select the variables utilized in these prior studies. In addition, I include some of the financial ratios found successful in prior bankruptcy prediction studies, as their selection of variables is non-overlapping with a strong theoretical underpinning (Altman and Sabato, 2007; Altman et al., 2010). These covariates essentially reflect six broad categories: profitability, liquidity, market timing activity, dividends, debt substitute, and investment[26] [27].

The effect of industry on the optimal choice of capital structure is highly debated in the literature. Frank and Goyal (2008) argue that industry is one of the most important factors that influence the optimum capital structure and that the effect of industry subsumes a number of factors that are of lesser importance. Moreover, Leary and Roberts (2010) report that year and industry fixed effects alone are enough to properly

[26] For more detailed theoretical discussion about the choice of these variables see El kalak and Hudson (2015a).
[27] For more details about variables' construction see table 5.2

explain debt choices. However, Graham and Leary (2011) and Minton and Wruck (2002) find contradictory evidence and report that capital structure extremes can exist within industries and that the variance of capital structure within industries is high and hard to explain empirically. I control for industry effects by classifying the SMEs into nine distinctive categories according to the SIC codes and including the variable as a factorial control variable.

In order to test the effect of profitability on the failure probability of debt and debt-free SMEs, I use four different proxies found to be significant in previous studies, namely, FCF, RETA, BIDTATA, and NIR. High values of FCF and BIDTATA signify high cash flow generating ability and better operating income utilization per unit of total assets; hence, one would expect the chance of default to be lower. The RETA ratio measures the cumulative profitability of the SME and its capacity to accumulate profit from sales. Therefore, a declining retained earnings is a sign of financial distress, hence, a negative relationship is expected between RETA and default probabilities. Higher values for both NIR and RDR usually indicate financially healthier firms thus a negative relationship is expected between these variables and the probability of SMEs' failure.

Baker et al. (2003) emphasize the importance of market timing in determining firms' capital structures. They find that firms issue equity when market values are high. In addition, Welch (2004) argues that debt levels in firms change according to the way shares are priced in the market. He finds that higher debt ratios are found in firms with under-performing shares, while lower levels of debt are found in firms with over-performing shares. Alti (2006), Flannery and Rangan (2006), Kayhan and Titman (2007), and Huang and Ritter (2009) also suggest that, within the pecking order theory of capital structure, firms adjust leverage in the opposite direction to their equity financing. This is also consistent with the trade-off model, with trade-offs between the tax advantages and default risk of debt on the one hand and the benefits of issuing or repurchasing equity by investors on the other hand (Huang and Ritter, 2009). To test for the effect of market valuation on the probability of bankruptcy I use the Market to Book (MB) ratio. This ratio is one of the most frequently used measures in capital structure research as a measure of the equity market valuation of the firm. A higher MB ratio indicates a better current market value for the firm; hence, one would expect the default probability to be lower.

The literature emphasizes the significance of the firm's size in its decisions about capital structure. For example a study by Bolton and Freixas (2000) finds that start up and small firms prefer to take loans or issue bonds to finance their investments in order to reduce their information dilution costs, however, due to their risky nature, accessing debt via loans or bonds is usually associated with high costs. In line with these findings Diamond (1991) argues that firms in their early life are most likely to be rejected for loans since they do not enjoy favourable track records of borrowing. Therefore, I hypothesize a negative relationship between the SMEs' size and their probability of failure. This hypothesis is well supported in previous literature such as Altman et al. (2010).

I use the cash, working capital, and tangible assets ratios as proxies for SMEs' liquidity. A healthier SME is expected to have a better liquidity position and hence higher liquidity ratios than a financially distressed SME. Therefore, I expect a negative relationship between liquidity ratios and the SME's probability of failure.

Regarding the activity ratios, I expect taxes to total assets to have a negative relationship with default probability, as healthy SMEs with a good financial position can generate more revenue and hence pay more tax than distressed SMEs. Moreover, the working capital to sales ratio is expected to have a negative relationship with bankruptcy probability, since higher levels of working capital to sales indicates better management of working capital and hence lower default probability.

Previous studies show that debt-free SMEs tend to pay more dividends than debt SMEs since the former have the need to satisfy shareholders so they can raise external equity on favourable terms, thus effectively replacing payouts to debt-holders with payouts to equity holders and without suffering the adverse effects of the agency problem of debt (see among others, (El kalak and Hudson, 2015b; Strebulaev and Yang, 2013)). Furthermore, it is believed that higher dividend payouts signal the firm's ability to generate profit and redistribute it in the form of dividends. Therefore, I hypothesise that dividend payments are negatively related to failure probability.

A study by Graham and Tucker (2006) reports that firms engaging in tax shelter activities reduce their debt levels. This view is further supported by the model of DeAngelo and Masulis (1980), which finds that NDTS substitute for interest tax deduction and firms with higher NDTS tend to become debt-free firms. To my knowledge, however, no previous research has attempted to answer the question of how NDTS affect the probability of failure for debt and debt-free SMEs. I hypothesise that NDTS positively affects the probability of failure, since it is viewed as a substitute for debt.

Stefanescu (2006) finds that pension plans have debt features as pension contributions are tax deductible. Hence, they are potentially regarded as important debt substitutes. Shivdasani and Stefanescu (2010) find that once pensions are considered, firms are less conservative in their choices of leverage than previously thought, and that they incorporate the magnitudes of pension liabilities in their capital structure decisions. However, not adjusting properly for these liabilities might lead to bankruptcies, such as those of GM and United Airlines. Therefore, it can be hypothesised that higher values of pension liabilities can lead to higher probabilities of failure.

Recently, the topic of operating leases has gained importance in capital structure studies. Similar to NDTS and pension liabilities, operating leases can both complement and substitute for traditional debt (Lewis and Schallheim, 1992; Graham et al., 1998; Yan, 2006; Eisfeldt and Rampini, 2009). Furthermore, scholars such as Rampini and Viswanathan (2010) and Rauh and Sufi (2012) argue that operating leases should be included in total debt valuation. Hence, I hypothesise that the probability of SME failure increases with higher values of operating leases.

To proxy for firm investment I use abnormal capital expenditure. According to Titman et al. (2004) increased capital expenditure should be viewed favourably in the market for a number of reasons. First, higher capital expenditures are likely to be associated with greater investment opportunities. Second, higher capital expenditures may also indicate that the capital markets, which provide financing for the investments, have greater confidence in the firm and its management. Hence, it can be argued that increased capital expenditure is associated with more profitability that leads to lower default probability. On the other hand, increased asset sales may be related to the need of a distressed firm to obtain more cash flow to maintain its operations. Therefore, a positive relationship is expected between assets sales and SMEs' probability of failure.

5.4. Methodology

5.4.1. Discrete-Time Duration-Dependant Hazard Model

5.4.1.1. The Hazard Model

The methodological approach used in this chapter is similar to that used in the third chapter section 3.2.1.1. This methodology is the discrete-time duration dependant hazard model.

The conditional probability of the discrete time hazard function (λ) for firm i to default in the time interval t, given it survives up to this time interval is as follows:

$$\lambda\left(t \backslash X_{i,t}\right) = \Pr(T = t \backslash T \geq t, X_{i,t}) \qquad (5)$$

T is a non-negative random variable that denotes the discrete failure time; T = t indicates failure within the time interval t and $X_{i,t}$ is the value of the covariates of firm i up to time interval t, whereas the hazard model can be expressed in the following equation:

$$h(t \backslash X_{i,t}) = h(t \backslash 0) \, . \exp\{X_{i,t}\beta\} \qquad (6)$$

where, $h(t \backslash X_{i,t})$ is the individual hazard rate of firm i at time t, $h(t \backslash 0)$ is the baseline hazard rate and $X_{i,t}$ is the vector of covariates of each company i at time t.

Because of its consistency with binary dependent variables and its time-series and cross-sectional features, the discrete hazard technique aligns with the characteristics of the bankruptcy data utilized. Additionally, in accordance with what has been discussed earlier, and to avoid the shortcomings of other statistical techniques, I evaluate hazard models in a discrete-time framework with random effects, thereby controlling for unobserved heterogeneity and shared frailty. Thus, the final equation's form is as follows, where a(t) is the time-varying covariate introduced to capture the baseline hazard rate and $P_{i,t}$ is the probability of experiencing the event by firm i at time t.

$$P_{i,t} = \frac{e^{\alpha(t) + \beta X_{i,t}}}{1 + e^{\alpha(t) + \beta X_{i,t}}} \qquad (7)$$

5.4.2. Performance Evaluation

Applying a bankruptcy out-of-sample prediction test, such as Shumway's (2001), enables us to measure the effectiveness of the models. The out-of-sample period is 2009 to 2013. The prediction test involves recalculating the forecasting models covering the period from 1980 till 2008, then dividing the firms into deciles based on their computed bankruptcy probabilities. The first decile is allocated for firms most likely to default in the subsequent year, the next most likely to default are put in the second decile, and so on. Subsequently, for each decile the percentage of firms that defaulted is reported. The model is considered to enjoy better classification performance the higher the percentage of firms that experience default in the top deciles. In addition to the out of sample test I provide the Akaike information criterion (AIC) value. This value indicates whether I have the appropriate model fit between the competing non-nested statistical models. This simple rule indicates that, the lower the value of AIC the better is the model's fit (see Mills (2011) for details)

5.5. Results and Discussion

In order to compare and highlight the main differences between the models for debt and debt-free companies I first perform univariate analysis of each individual covariate from my broad list of ratios followed by a correlation test for each of the two groups separately. Descriptive statistics analysis is presented for the final selected explanatory variables that are fitted into the multivariate models. This is followed by the development of my main multivariate models for debt and debt-free companies. Finally, I discuss the out of sample classification performance for the models developed.

5.5.1. Univariate analysis

I start my investigation by reporting the estimates obtained from the univariate analysis and their corresponding chi-squared values provided in table 5.2. This analysis is conducted prior to the development of the final multivariate models. Univariate analysis has been widely recommended and used in the literature to obtain an initial understanding about the discriminate power of the explanatory variables (Nam et al., 2008; Altman et al., 2010; El kalak and Hudson, 2015a). I choose each covariate in turn as an independent variable and perform univariate regression to have an initial understanding about the direction and significance of the relationship with the dependant variable (fail==1 and non-fail==0). Covariates that exhibit the expected sign with significant discriminatory power when estimated using the discrete-hazard model will enter the final multivariate model. In line with previous studies I expect covariates under profitability, liquidity, market timing, activity, dividends, and investment to have a negative relationship with SMEs' default probabilities. On the other hand, I expect debt substitute covariates and AS to enjoy a positive relationship with SMEs' default probabilities.

A general overview of table 5.2 shows that within the profitability ratios all of the covariates have the expected sign with significant discriminatory power except for RETA which exhibits a positive and insignificant relationship with the default probability.

Moreover, within the liquidity ratios, I expect the coefficient of TA to be negative given that higher levels of tangibility mitigate moral hazard and adverse selection problems (Sogorb-Mira, 2005) which might lead to lower bankruptcy probabilities. However, TA enjoys a significantly positive relationship with the probability of bankruptcy for both debt and debt-free SMEs. A similar finding is reported by Chung et al. (2013) who find a positive but insignificant relationship between tangible assets and failure probability using a sample of firms from the oil industry. One possible explanation might be that higher tangible assets give an indicator of lower efficiency in the utilisation of the SME's available assets and hence lower returns which eventually might lead to an increase in financial problems. The variables Cash and WCTA show the expected negative sign for both debt and debt-free SMEs.

Activity ratios, namely, WCSALE and TTA have negative and highly significant power for both groups. Each of Size, MB and DR ratios exhibits the appropriate sign (except for DR in the Debt-free group) but with insignificant discriminatory power for both groups suggesting that size, market to book ratio and dividend payments do not play a significant role in differentiating between failed and non-failed SMEs for both debt and debt-free groups.

Moreover, I find that NPL and OL5 are both insignificant for the debt-free group while they show significantly positive relation with the binary default indicator for debt SMEs.

Finally, after analysing the univariate regression for each covariate, the following covariates are tested to detect any multicollinearity: FCF, BIDTATA, NIR, RDR, Cash, WCTA, TA WCSALE, TTA, NDTS, ABCE and AS for the debt-free group, while I add NPL and OL5 for the debt group.

Table 5.2 univariate analysis
This table reports the coefficients obtained from univariate regression analysis of respective covariates for both, debt and debt-free SMEs as discussed in section (2). For each group the coefficients are estimated using discrete-time duration-dependant hazard function. ***, **, * indicates that the coefficient is significant at 1%, 5%, and 10% respectively.

Ratio	A Priori	Debt		Debt-Free	
		β	Wald Chi^2	β	Wald Chi^2
Profitability					
FCF	(-)	-.6972913***	43.39	-0.4745401***	6.49
BIDTATA	(-)	-.3711323***	17.36	-.3273681**	4.3
RETA	(-)	0.0002509	2.92	0.0003532	2.32
NIR	(-)	-2.105886***	27.20	-2.780654***	13.47
RDR	(-)	-2.074049***	11.2	-2.277114***	6.01
Size					
Size	(-)	-0.0199564	0.34	-0.1016578	3.46
Liquidity					
Cash	(-)	-2.385026***	31.63	-1.691522***	14.54
WCTA	(-)	-.0028451***	21.41	-.0024563***	8.55
TA	(-)	1.552676***	35.76	1.909333***	11.47
Market Timing					
MB	(-)	-0.0135554	2.54	-0.0228389	1.91
Activity					
WCSALE	(-)	-.5315717***	40.70	-.4199026***	10.78
TTA	(-)	-.1032646***	14.54	-.1903705***	9.47
Dividends					
DR	(-)	-.1028714	0.01	2.09342	1.93
Debt Substitute					
NDTS	(+)	3.864606***	35.42	8.069832***	39.36
NPL	(+)	9.13969***	12.29	3.313744	0.24
OL5	(+)	.7046599**	5.07	-.5854416	0.41
Investments					
ABCE	(-)	-.9106641**	5.60	-2.066186*	4.44
AS	(+)	6.091186***	26.27	8.107622***	13.44

5.5.2. Correlation and Descriptive Statistics

The correlation matrices presented in table 5.3, provide details about the level of collinearity among the selected covariates. Panel A of the table shows the correlations for debt-free SMEs and panel B for SMEs with debt. When two covariates are highly correlated with each other I keep the covariate that enjoys a higher Wald chi-square value obtained from the univariate test table. Out of the twelve covariates selected for the debt-free group, the highest correlation of about 0.912 can be found between FCF and BIDTATA. Since FCF enjoys a higher wald chi-squared I drop the BIDTATA variable due to multicollinearity. A number of other covariates also have a certain degree of multicollinearity but I keep these pairs since the level of correlation is not too high, such as the correlation between RDR and FCF (-0.400), WCTA and WCSALE (0.438), and TA and NDTS (0.400). Regarding the debt SMEs group, I again find a high correlation between FCF and BIDTATA (0.929) and since FCF has a higher Wald chi-squared I keep FCF in my multivariate model. Therefore, eleven variables are entered into the final multivariate model for debt-free SMEs, while the final debt SMEs model consists of thirteen variables. However, it should be noted that some of these variables may not be significant in the final multivariate models due to multicollinearity between the explanatory variables.

An initial understanding about the descriptive statistics of the covariates used in this study is useful in understanding any potential biases and variability that may arise among the variables in the multivariate models. Table 5.4 reports the mean values and standard deviations of the final explanatory variables employed in this study. A general overview of the descriptive analysis for the covariates selected shows evidence of differences between the corresponding variables in the two SMEs groups, which might be an indicator that the factors influencing failure probability differ between the debt and debt-free groups. For example, the mean of Cash for failed SMEs in the debt-free model (0.237) is higher than its counterpart in the debt model with only 0.075. The means of WCTA in the debt-free sample for both failed and non-failed SMEs are more than double those of their counterparts in the debt sample. This may be an indicator of better efficiency in running their working capital and hence more protection against bankruptcy. In addition, tangible ratios for debt SMEs are higher than for debt-free SMEs which might explain the tendency for debt SMEs to prefer debt over equity in their financing activities, since high levels of tangible assets are preferable to obtain cheaper debt financing. However, for both debt and debt-free samples the mean of tangible assets for failed SMEs is higher than for their non-failed counterparts. This may be explained on the basis that excessive levels of tangibility might increase the probability of bankruptcy.

In line with the economic hypotheses and previous studies such as Altman and Sabato (2007) and El kalak and Hudson (2015a) I expect the means of the covariates which are positively related to default probability (e.g. TA, NDTS, NPL, OL5, and AS) to be to higher for the failed group than the non-failed group for both debt and debt-free SMES. For example, the mean of asset sales for the failed groups are higher than in the non-failed groups. This might be related to the need of failed SMEs to obtain more cash flow to maintain their operations or selling their assets for bankruptcy requirements. Furthermore, within the failed groups, the mean of asset sales is higher for debt-free SMEs with a mean value of 0.028, compared to 0.023 for debt SMEs. This increase in asset sales may reflect a higher probability of failure for failed debt-free SMEs.

Similarly lower means are expected for the covariates in the failed groups compared to those in the non-failed groups when these covariates are negatively related to failure probability such as FCF, NIR, RDR, Cash, WCTA, WCSALE, TTA, and ABCE. I notice that non-failed SMEs for both debt and debt-free groups invest substantially in R&D activities compared to failed groups. The means of non-failed R&D for debt and debt-free groups are 0.0826 and 0.121, respectively, while the means of failed R&D for debt and debt-free are 0.042 and 0.044, respectively.

Table 5.3 correlation matrix for Debt-Free SMEs (Panel A)
This table provides the correlation matrix for the covariates for the debt-free sample used in this study. * indicates that the correlation is significant at 1%.

	FCF	BIDTATA	NIR	RDR	CASH	WCTA	TA	WCSALE	TTA	NDTS	ABCE	AS
FCF	1											
BIDTATA	0.9219*	1										
NIR	0.0779*	0.0602*	1									
RDR	-0.4009*	-0.3680*	0.0126	1								
CASH	-0.2229*	-0.2116*	-0.1905*	0.2229*	1							
WCTA	0.0232*	0.0420*	0.0958*	0.2722*	0.2158*	1						
TA	0.0613*	0.0473*	0.0913*	-0.1461*	-0.3062*	-0.3382*	1					
WCSALE	-0.1392*	-0.1182*	0.0802*	0.3089*	0.2601*	0.4384*	-0.1372*	1				
TTA	0.3094*	0.3167*	0.0196	-0.1351*	-0.1096*	0.2861*	-0.1894*	-0.1868*	1			
NDTS	-0.1067*	-0.1190*	0.0071	0.0481*	-0.1884*	-0.1849*	0.4005*	-0.1377*	-0.0978*	1		
ABCE	-0.0240*	-0.017	0.1954*	0.1175*	-0.0822*	-0.0237*	0.2064*	0.0002	-0.0002	0.1106*	1	
AS	0.0354*	0.0392*	0.2728*	-0.0215*	-0.0992*	0.0964*	0.0244*	0.0568*	0.0126	0.0526*	-0.0096	1

Table 5.3 correlation matrix for Debt SMEs (Panel B):
This table provides the correlation matrix for the covariates for the debt sample used in this study. * indicates that the correlation is significant at 1%.

	FCF	BIDTATA	NIR	RDR	CASH	WCTA	TA	WCSALE	TTA	NDTS	NPL	OL5	ABCE	AS
FCF	1													
BIDTATA	0.9299*	1												
NIR	0.0507*	0.0211*	1											
RDR	-0.4531*	-0.4286*	-0.0051	1										
CASH	-0.2839*	-0.2801*	-0.0807*	0.3480*	1									
WCTA	-0.0051	0.0113*	-0.0018	0.2713*	0.2788*	1								
TA	0.1230*	0.1151*	0.1877*	-0.2060*	-0.2820*	-0.3161*	1							
WCSALE	-0.0333*	-0.0121*	0.0583*	0.3563*	0.3444*	0.5094*	-0.1829*	1						
TTA	0.2192*	0.2222*	-0.0448*	-0.1114*	-0.0737*	0.3352*	-0.2371*	-0.0365*	1					
NDTS	-0.1547*	-0.1679*	0.0299*	0.0535*	-0.1146*	-0.1688*	0.3522*	-0.1407*	-0.1339*	1				
NPL	0.0670*	0.0747*	-0.0629*	-0.0602*	-0.0499*	-0.0066	0.0105*	-0.0325*	0.0567*	-0.0081	1			
OL5	-0.1609*	-0.1504*	0.0008	0.1497*	0.0147*	-0.0539*	-0.0459*	-0.0301*	-0.0600*	0.1149*	-0.0445*	1		
ABCE	-0.0105*	-0.0099	0.3256*	0.0689*	-0.0386*	-0.0144*	0.1842*	0.0228*	-0.0274*	0.0474*	-0.0179*	0.0555*	1	
AS	0.0129*	0.0121*	0.0501*	-0.0274*	-0.0410*	0.0274*	0.0617*	0.0367*	-0.0271*	0.0708*	-0.0121*	-0.0058	0.0005	1

Table 5.4 descriptive statistics
This table reports the descriptive statistics of the key independent variables used in the debt and debt-free Models, for failed and non-failed groups. The third and fourth columns report the mean and standard deviation of the variables for failed and non-failed debt SMEs, while the fifth and sixth columns report the mean and standard deviation of the variables for failed and non-failed debt-free SMEs.

Variable		Debt		Debt-Free	
		Mean	SD	Mean	SD
FCF					
	Failed	-0.31082	0.600352	-0.2890229	0.63562
	Non-Failed	-0.18985	0.518502	-0.2195937	0.534213
NIR					
	Failed	0.070308	0.146406	0.0455867	0.162511
	Non-Failed	0.104452	0.150589	0.0941442	0.164216
RDR					
	Failed	0.042931	0.108918	0.0443059	0.120872
	Non-Failed	0.082648	0.141041	0.1218702	0.157761
Cash					
	Failed	0.074902	0.158473	0.2374353	0.339271
	Non-Failed	0.138558	0.200628	0.2944064	0.284867
WCTA					
	Failed	51.14391	155.762	107.0289	232.2313
	Non-Failed	101.4111	191.5673	226.5413	282.2933
TA					
	Failed	0.349023	0.288462	0.1796042	0.25961
	Non-Failed	0.263193	0.248266	0.1436288	0.198196
WCSALE					
	Failed	0.032505	0.933674	0.5756322	1.493545
	Non-Failed	0.542555	1.360967	1.361596	1.778148
TTA					
	Failed	1.095228	3.0545	1.071046	2.98783
	Non-Failed	1.774621	3.667066	2.628534	4.478082
NDTS					
	Failed	0.081908	0.093895	0.0664124	0.111796
	Non-Failed	0.065287	0.07203	0.0488968	0.069147
PNL					
	Failed	0.007611	0.034439		
	Non-Failed	0.004188	0.024431		
OL5					
	Failed	0.113824	0.225214		
	Non-Failed	0.094177	0.16696		
ABCE					
	Failed	-0.87286	0.147187	-0.9224675	0.123323
	Non-Failed	-0.8612	0.136691	-0.8855612	0.127173
AS					
	Failed	0.023783	0.048265	0.0283447	0.056196
	Non-Failed	0.014546	0.038497	0.0179462	0.046352

5.5.3. The Discrete-Time Duration-Dependant Hazard Models

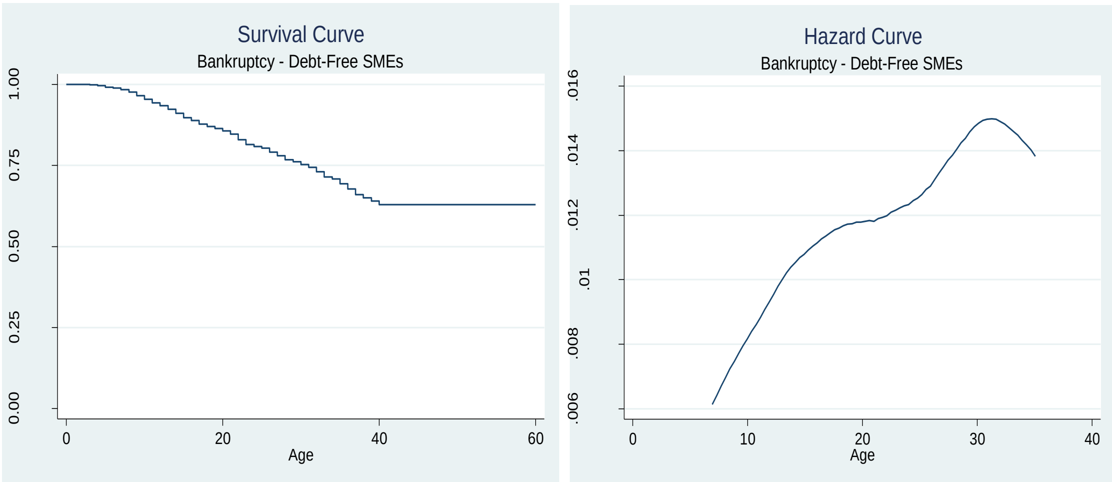
I develop two bankruptcy prediction models, one for the debt, and one for the debt-free SMEs samples. The dependant variable in both models has binary outcomes (fail and non-fail), and the explanatory variables are the set of covariates analysed in section 5.2.The covariates selected to enter the multivariate models are chosen after consideration of their significance and correlation with other potential variables. The first step in this section is the detection of the baseline hazard rate, which is the cornerstone to further develop the discrete-time duration-dependant hazard models. This is followed by the development and discussion of the final multivariate models for each group.

5.5.3.1.Determination of Baseline Hazard Rate

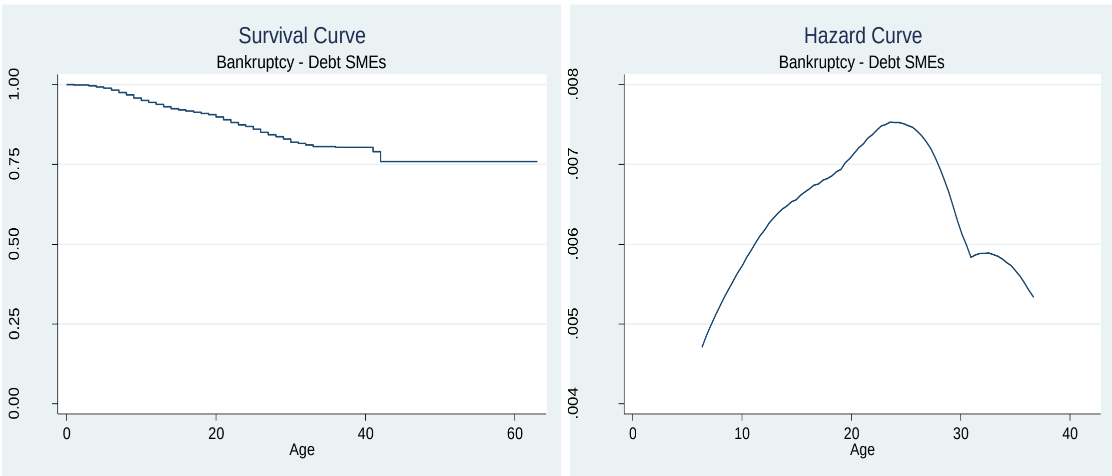
There are different methods, as explained in section 3.3.2.2 for construction of the baseline hazard rate for both multivariate models. However to choose between these methods, first I have to estimate and analyse the survival and hazard curves for each model. Figure 5.1 provides the estimated curves based on the Kaplan-Meier estimator for both debt-free and debt models. The survival probability for the debt-free SMEs model tends towards 0.60 as the SME age approaches 40 and remains constant until the SME's age reaches 60. However, the survival probability for debt SMEs gradually declines towards 0.75 until the SME's age becomes slightly over 40 then continues with the same survival probabilities until the SME's age becomes 60. The different behaviours of the survival curves for each model indicate that the survival attributes may be different for each SME group. Although the survival curves give us an initial understanding about the relationship between survival probabilities and the SME's age, it is important to plot the hazard curve for each model in order to decide the most appropriate method of calculating the baseline hazard. From figure 5.1 I can deduce that different baseline hazard rate specifications are required for each model since each hazard curve exhibits a different functional relationship with the age of the SMEs. Moreover, since all the hazard curves show non-constant hazard rates for any defined age group a piecewise-constant method is inappropriate for this calculation. Therefore I use a fully non-parametric baseline hazard specification using age specific dummy variables to specify the baseline hazard rate. The minimum age of a SME in my sample is 1 while the maximum age is 64. Therefore, I generate 63 age specific dummies to represent all age categories.

Figure 5.1 survival and hazard curves

A. Debt-Free SMEs Survival and Hazard curves



B. Debt SMEs survival and Hazard curves



5.5.4. Discrete-time Duration-dependant Hazard Models

5.5.4.1. Hazard Model for Debt-Free SMEs

This model has been estimated for the debt-free SMEs sample, which contains companies with neither current nor long –term debt in a given year. I eliminate the covariates NPL and OL5 from my list of potential explanatory variables because, as discussed above, they do not provide statistically significant discriminatory power under the univariate analysis. Moreover, the variable BIDTATA is eliminated because of high correlation with other covariates. Thus, the final model for debt-free SMEs is estimated using eleven explanatory variables. The results are reported in table 5.5, which shows that all the selected covariates have the expected sign in relation to the default probability. However, I notice that R&D, WCTA, TA, WCSALE, and AS do not provide statistically significant power in explaining the default probability of debt-free SMEs. As expected, tangible assets does not play a significant role in determining the probability of bankruptcy given that debt-free SMEs do not have a sufficient amount compared with debt SMEs, which rely heavily on tangible assets as collateral for obtaining external financing. On the other hand, I find that higher values of free cash flows and net investment opportunities significantly decrease the probability of failure for debt-free SMEs. Furthermore, the liquidity variable Cash is highly significant in my multivariate model, highlighting the importance of liquidity in the survival of debt-free SMEs.

5.5.4.2. Hazard Model for Debt SMEs

This model has been estimated for the debt SMEs sample, which contains companies with current and/or long –term debt in a given year. I develop the model using a similar approach to that used in building the model for debt-free SMEs. Both variables, NPL and OL5, which were eliminated in my previous model, are included in this model since they are found to have a significant impact on debt SMEs' probability of failure in the univariate analysis. Furthermore, I again omit the BIDTATA covariate as it is highly correlated with other covariates. Thus, the final model for debt SMEs is estimated using thirteen explanatory variables. The results reported in table 5.5 show different determinants of the probability of bankruptcy for debt SMEs compared to those affecting debt-free SMEs. For example, tangible assets play a significant role in differentiating between failed and non-failed debt SMEs. This is probably due to the importance of tangible assets in facilitating access to external financing. Moreover, asset sales are found to significantly affect the probability of failure for debt SMEs, unlike the findings for debt-free SMEs. Furthermore, R&D expenses are negatively related to the probabilities of failure for both groups, one explanation is that financially secure companies feel more able to invest in R&D. Moreover, R&D expenses are found to significantly affect the failure probabilities of debt SMEs, with more R&D expenditures increasing the survival probabilities of debt SMEs. Both NDTS and NPL are found to positively affect the failure probabilities of debt SMEs, whereas OL5 fails to exhibit significant discriminatory power.

Table 5.5 multivariate hazard models
This table shows the multivariate discrete-time duration-dependant hazard models developed for debt-free and debt SMEs. The first column lists the variables studied, the second and fourth reports the coefficients. ***, **, * indicates significance at 1%, 5%, and 10% level respectively. In addition, the last 6 rows report the goodness of fit measures and number of observations.

	Debt-Free Model		**Debt Model**	
FCF	-0.867***		-1.110***	
	(0.304)		(0.142)	
NIR	-2.651***		-1.313***	
	(1.012)		(0.484)	
RDR	-1.729		-1.870**	
	(1.431)		(0.752)	
Cash	-1.930***		-2.231***	
	(0.651)		(0.516)	
WCTA	0.00125		0.000591	
	(0.00139)		(0.000823)	
TA	1.193		0.859**	
	(0.957)		(0.338)	
WCSALE	-0.395*		-0.425***	
	(0.208)		(0.113)	
TTA	-0.305***		-0.0792**	
	(0.101)		(0.0376)	
NDTS	7.847***		1.687**	
	(1.945)		(0.794)	
NPL			12.18***	
			(2.847)	
OL5			0.241	
			(0.357)	
ABCE	-3.235**		0.0731	
	(1.393)		(0.459)	
AS	1.632		4.456***	
	(3.361)		(1.362)	
Macroeconomic	0.279***		0.210***	
	(0.0974)		(0.0399)	
Constant	-15.95***		-24.42	
	(5.639)		(3.551)	
Age Dummies	Yes		Yes	
Goodness of Fit	**Value**	**P-Value**	**Value**	**P-Value**
Wald Chi^2	151.31	0	307.83	0
Log Likelihood	-679.97405		-2213.096	
AIC	4544.192		1475.948	
BIC	5075.751		1916.843	
Firm-Year Observations	18,653		75,836	
Number of SMEs	3,967		10,302	

5.5.5. Model Forecasting Accuracy

As mentioned in section 5.4.2 I use out of sample prediction to test the effectiveness of the models developed in the prediction of SMEs' bankruptcy. Table 5.6 provides the classification performance measure for each of the prediction models developed. In terms of the models' classification performance I find that both models developed are able to capture more than 60% of the distressed SMEs in the top three deciles, which is considered to be a good percentage, whereas the total number in the last five percentiles is less than 20%. The value of AIC is around 1475 for debt model but for debt-free model it is around 4544, which emphasise that debt model provides a better fit than the debt-free model.

Table 5.6 classification performance measure
This table reports the classification performance measures for debt-free and debt SMEs for the period from 2009 till 2013. The values are cumulative classification measures over the ten deciles.

Decile	Debt-Free	Debt
1	30.00%	43.33%
2	26.67%	20.00%
3	10.67%	12.00%
4	12.00%	8.00%
5	4.00%	4.00%
6 , 10	16.66%	12.67%
Total	100.00%	100.00%

5.6. Further Analysis

This section attempts to provide further analysis on the failure probability of debt and debt-free SMEs by testing the effect of different SMEs' size on their failure probabilities. So from this analysis I aim to achieve two objectives. First, it is argued that using debt increases with the increase in the firm's size as the firm is in a better position to take loans or issue bonds and as per the trade-off theory this increase in using debt may lead to an increase in the firm's probability of bankruptcy (Altman et al., 2010). Building on this argument, I control for debt (by dividing the sample into debt and debt-free SMEs) and test whether any differences exists between the probabilities of bankruptcy for debt-free SMEs across their different size segments. Second, I also test whether any differences exist when modelling the probability of bankruptcy between the debt and debt-free SMEs across the size segments which may help regulators and lenders to take into account the different size segments while designing future regulations or planning risk management models.

The sample for debt and debt-free SMEs is divided into three size categories, namely, micro, small, and medium. The micro firms consists of less than 20 employees; firms are classified as "Small" if they have greater than or equal to 20 but less than 100; and "Medium" if they have greater than or equal to 100 and less than 500 employees[28].

According to table 5.7, a general overview of the three models for the debt-free SMEs shows that different size segments affect the bankruptcy probabilities differently. For example, TA significantly affects the bankruptcy probabilities for medium SMEs while it does not show any significant effect on both micro and small SMEs. This may be related to the fact that larger SMEs tend to show higher tangible assets than their smaller counterparties. NIR has a significantly negative effect on the probability of bankruptcy for micro SMEs while it does not significantly affect both small and medium SMEs. RDR does not enjoy a significant effect on both micro and small SMEs unlike medium SMEs. WCTA, Cash, WCSALE, and ABCE show the appropriate significant sign for both micro and small SMEs while they fail to show any significant relation with the bankruptcy probabilities for medium SMEs. Furthermore, the differences in the models are not only limited to whether the variables enjoy a significant relationship with the bankruptcy probabilities but also with the values of their coefficients. For example, the NDTS variable enjoys a significantly positive relation with the bankruptcy probabilities for all the three models. However, the

[28] For more details about the SMEs size classification see El Kalak and Hudson (2015a).

coefficient's magnitude is different between micro, small, and medium and the same findings holds for FCF. Therefore, it can be concluded that bankruptcy probabilities should be modelled separately for debt-free SMEs according to the size segments and any risk assessment valuation should be considered separately for these categories.

Moreover, while conducting a cross comparison among the different size models between debt and debt-free SMEs groups, it is clear that there are differences for some variables in each model such as AS in micro SMEs, where it shows a significant relationship with the probabilities of bankruptcy for the debt SMEs while it does not show any significant relationship for the debt-free SMEs. Similar differences can be found between RDR, WTCA, TA, ABCE, and AS for small and medium sized debt and debt-free SMEs.

Table 5.7 hazard models according to SMEs' size segments
This table shows the multivariate discrete-time duration-dependant hazard models developed for each size segment of debt-free and debt SMEs. Three size segments are reported for each group of SMEs, namely, micro, small, and medium. The first column lists the variables studied, the second third and fourth report the coefficients for debt-free SMEs and the fifth, sixth, and seventh columns report the coefficients for debt SMEs. ***, **, * indicates significance at 1%, 5%, and 10% level respectively. In addition, the last 6 rows report the goodness of fit measures and number of observations.

	Debt-Free SMEs			**Debt SMEs**		
	Micro	Small	Medium	Micro	Small	Medium
FCF	-0.368***	-2.460***	-6.005***	-0.627***	-1.666***	-2.301***
	(0.268)	(1.551)	(4.488)	(0.200)	(0.390)	(0.476)
NIR	-2.314**	-0.801	-13.36	-2.224***	-1.603	-0.841
	(1.125)	(3.460)	(11.14)	(0.787)	(1.233)	(1.119)
RDR	-0.644	-12.36**	-5.601**	-0.761	-4.510**	-5.458**
	(1.362)	(5.792)	(12.48)	(1.009)	(2.016)	(2.599)
Cash	-1.491**	-4.817*	-19.88	-1.844***	-10.27***	-0.604
	(0.587)	(2.723)	(15.57)	(0.675)	(2.417)	(1.399)
WCTA	0.00299**	0.00781**	0.00106	0.00230**	0.000319	0.00399
	(0.00127)	(0.00370)	(0.0105)	(0.00112)	(0.00283)	(0.00270)
TA	0.889	0.669	15.03**	0.0172	1.827**	1.554***
	(0.798)	(3.825)	(6.054)	(0.473)	(0.907)	(0.952)
WCSALE	-0.446***	-1.370*	-2.365	-0.372***	-0.891***	-0.458***
	(0.163)	(0.743)	(2.147)	(0.141)	(0.329)	(0.383)
TTA	-0.108	-0.304	-0.114	-0.0723	-0.0561	-0.0510
	(0.0873)	(0.258)	(0.367)	(0.0558)	(0.108)	(0.0813)
NDTS	5.203***	16.03***	18.89***	1.749**	1.410**	3.402**
	(1.609)	(8.098)	(16.35)	(1.027)	(2.495)	(2.634)
LwPNL				8.944***	17.57**	19.65***
				(7.145)	(8.433)	(5.043)
LwOL5				0.624	1.157	0.190
				(0.525)	(1.121)	(0.829)
ABCE	-2.329**	-4.508**	-12.90	1.354*	-0.700	0.772
	(1.447)	(4.093)	(13.31)	(0.740)	(1.104)	(1.022)
AS	3.201	15.11	7.475	0.797***	2.998**	11.38***
	(3.126)	(15.81)	(24.80)	(2.189)	(3.792)	(2.989)
Macroeconomic	0.309***	0.448*	1.656**	0.421***	0.360***	0.0286***
	(0.101)	(0.342)	(0.894)	(0.0697)	(0.109)	(0.0825)
Constant	-10.28**	-3.873	-24.48*	-24.20**	-11.83***	-10.01***
	(4.506)	(6.143)	(13.86)	(4,556)	(2.730)	(2.727)
Age Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Goodness of fit						
Wald Chi^2	83.22***	58.29**	30.63**	113.14***	84.05***	106.62***
Log Likelihood	-442.94825	-219.40831	-119.2511	-920.39373	-533.63918	-657.44229
AIC	997.8965	508.8166	374.5022	1944.787	1163.278	1422.885
BIC	1364.22	917.1582	554.3334	2340.055	1535.621	1863.963
Firm-Year Observations	9842	5673	3138	16988	27594	31258
Number of SMEs	1876	1109	982	2477	3713	4112

Table 5.8 definition of variables

Code	Name	Definition	Compustat item code
Profitability			
FCF	Free Cash Flow	I follow Frank and Goyal's (2008) definition:	
	1	For SMEs reporting format codes (SCF = 1 to 3): FCF = Income before extra items + Discontinued Operation + Depreciation and Amortization + Deferred Taxes + Equity in Net Loss + Gain/Loss from PPE + Other funds from operations + Other sources of funds	FCF = IBC+XIDOC+DPC+TXDC+ESUBC +SPPIV +FOPO+FSRCO
	2	For SMEs reporting format codes (SCF = 7): FCF = Income before extra items + Discontinued Operation + Depreciation and Amortization + Deferred Taxes + Equity in Net Loss + Gain/Loss from PPE + Other funds from operations + Exchange Rate Effect	FCF = IBC+XIDOC+DPC+TXDC+ESUBC +SPPIV +FOPO+EXRE
BIDTATA		Operating income before depreciation/Total Assets	OIBDP/TA
RETA		Retained earnings / Total Assets	RE / AT
NIR	Net Investment Ratio	Net Investment / Total Assets	NI = NI/AT
RDR	Research and Development	Research and Development Expenses/Total Assets	XRD/AT
Size			
Size	SME's Size	Log(Total Assets)	log(TA)
Liquidity			
Cash		Cash and marketable securities / Total Assets	(CH+MSA)/AT
WCTA		Working capital / Total Assets	WCAP/AT
TA	Tangible Assets	Tangible Assets / Total Assets	TA = PPENT/AT
Market Timing			
MB	Market to Book Ratio	Market value of Total Assets/Total Assets	MB=MVTA/AT
Activity			
WCSALE		Working Capital / Sales	WCAP / SALE
TTA		Taxes / Total Assets	TXT / TA
Dividends			
DR	Dividend Ratio	Dividend/Total Assets	DR=DV/AT
Debt Substitute			
NDTS	Net Debt Tax Shield	(Depreciation and Amortization + Deferred Tax and Investment Tax Credit)/ Total Assets	NDTS = (DP+TXDITC)/AT
NPL	Net Pension Liabilities	Pension Obligations - Pension Assets, if Pension obligations are greater than or equal to Pension Assets, and as zero otherwise	max(PO-PA,0)
OL5	Five Years Operating Leases	Five Years Lease Commitments / Total Assets	OL5=MRCT/AT
Investments			
ABCE	Abnormal Capital Expenditure	Definition according to Titman et al. (2004)	(CEt/(CEt-1 + CEt-2 + CEt-3)/3) -1
AS	Asset Sales	(Sale of Property + Sale of Investments)/Total Assets	AS=(SPPE+SIV)/AT

5.7. Conclusion

This chapter investigates the effect of the debt-free decision on the default risk of SMEs in the US market and how this substantial deviation from the optimal capital structure affects the probabilities of failure of SMEs compared to their leveraged counterparts. To address this issue I classify my SMEs sample into two categories (Debt-Free and Debt) while modelling bankruptcy prediction. Then I attempt to capture any differences, between these two models to identify the main determinants and to what extent they affect the failure probabilities for each of the studied groups.

I apply discrete-time duration-dependent hazard rate modelling techniques to develop separate bankruptcy prediction models for debt and debt-free SMEs respectively. My empirical analysis is performed using panel data available to us from the Compustat database. The sample employs annual firm-level data for 95,110 firm-year observations, covering an analysis period from 1980 to 2013. This sample is divided into two main groups, namely, the debt group containing 76,457 firm-year observations and the debt-free group containing 18,653 firm-year observations. Furthermore, within each group I classify SMEs into failed and non-failed SMEs. There are 309 firm-year observations representing the failed debt-free SMEs and 622 firm-year observations representing the failed debt SMEs. Small and medium-sized enterprises are defined as firms with fewer than 500 employees and average annual receipts of less than $ 7.5 million.

In order to test the effectiveness of the models developed in the prediction of SMEs bankruptcy and their forecasting abilities I perform a bankruptcy out-of-sample prediction test similar to Shumway (2001). I specify my out-of-sample period to be from 2009 to 2013. Therefore, I re-calculate all the forecasting models for the period from 1980 to 2008 and then year by year I rank the SMEs into deciles based on their computed bankruptcy probabilities. The SMEs most likely to default in the subsequent year are placed into the first decile, the next most likely to default in the second decile, and so on. Hence, the higher percentage of SMEs that experience default in the top deciles reflects a model with better classification performance. Both multivariate models developed exhibit strong classification performance, capturing more than 60% of the distressed SMEs in the top three deciles, which is considered to be a good percentage whereas the total number of the last five deciles is less than 20%.

A comparison of the default prediction models for debt and debt-free samples suggests that different sets of explanatory variables affect the default probabilities for these SMEs. My empirical findings clearly show that four explanatory variables, namely, RDR, TA, ABCE, and AS affect the probability of bankruptcy differently for each model, thus suggesting a potential need to treat debt and debt-free SMEs separately while modelling credit risk. Furthermore, I investigate how different size categories may influence the failure probabilities for each of the debt and debt-free group by dividing the sample into micro, small, and medium SMEs. The findings indicate that bankruptcy probabilities should be modelled separately for debt and debt-free SMEs according to the size segments and any risk assessment valuation should be considered separately for these categories.

Chapter 6

6. Conclusion

The aim of this thesis has been to provide additional insights into the understanding of a number of issues relating to the credit risk modelling and capital structure decisions of SMEs in the US market. As highlighted in prior research, SMEs constitute a vibrant sector of the worldwide economy and the SMEs' business has been associated with certain unique characteristics.

6.1. Research Findings

In this thesis I have presented three empirical chapters on the SMEs' credit risk modelling and capital structure.

My research interest in the first empirical chapter stems from the huge diversity of firm size that exists within the SMEs category. SMEs can be divided into micro, small, and medium sized firms. This chapter attempts to investigate the extent to which the different size categories affect the SMEs' probabilities of bankruptcy.

To examine this, I forecast the bankruptcy probabilities by developing three discrete-time duration-dependant hazard models namely Micro, Small, and Medium. These models' performance is then compared with the model developed for SMEs as a whole. Then, I estimate the insolvency hazard models after considering the correlation among the covariates. Finally, I compare my main three estimated models (micro, small, and medium) with the SMEs model to identify the common default attributes. The analysis is carried out on a sample of (11,117) US non-financial firms, of which (465) are defaulted firms, spanning the time period from 1980 till 2013. To validate the out-of-sample prediction performance of the models the entire study window is divided into two groups: the estimation period (1980-2008, 28 years) for the model building and the forecasting period (2009-2013, 5 years) for the out-of-sample forecasting performance test.

My empirical findings show that significant differences exist between the bankruptcies attributes of micro and small firms on the one hand and SMEs firms on the other. Therefore, a separate treatment should be provided when modelling for the credit risks of these categories. Moreover, I find similar results to that found by Gupta et al. (2014) that the explanatory power of financial reports increases with the size of the firm. I find that medium and SMEs bankruptcy attributes have almost an identical set of explanatory power, leading us to believe that differentiating between these two groups has no material impact on the decision making process, unlike differentiating between the micro and small SMEs. Finally, I have provided an out of sample validation following the Shumway (2001) measure. My out of sample results show good performance classifications for the four bankruptcy prediction models developed.

The second empirical chapter is motivated by the growing popularity of debt-free firms and the accompanying increase in the literature investigating the reasons behind this choice. An increasing body of literature focuses on the determinants of SMEs' capital structure in the US (e.g. Berger and Udell (1998)), Europe (e.g. Sogorb-Mira (2005); Ramalho and da Silva (2009)), and Asia (e.g. Matlay et al. (2006)). However, to my knowledge there has been no study yet that tried to explore the zero-debt puzzle of SMEs. Therefore, in this study, I attempt to provide potential explanations for the reasons behind the choice of zero-debt along various dimensions and examine a number of economic mechanisms that I believe further explain the phenomenon of extreme debt conservatism in SMEs. Furthermore, I study to what extent different SMEs size segments (namely micro, small, and medium) affect the debt-free decision. The extreme debt puzzle refers to the idea that certain firms prefer to have no leverage compared to that which would maximize the firm value from a static trade-off theory point of view

(Miller, 1977; Graham, 2000). To undertake this analysis, I employ data extracted from the Compustat database for the period from 1980 to 2014. My data consists of all available annual information for US SMEs. The dataset consists of (95,450) firm-year observations, of which there are (18,764) debt-free firm-year observations.

I find that on average 20% of firm-year observations over the whole sample period from 1980 to 2014 exhibit zero-debt behaviour, and this percentage is increasing across each size segment from micro, small, to medium, providing initial evidence that the larger the firm, the easier its access to debt and hence its chances to use debt increase. Moreover, it is found that the debt-free phenomenon is relatively persistent; for more than 95% of SMEs in my sample, the maximum number of debt-free years is seven years.

I test empirically the theoretically derived elements that might affect the capital structure decisions within the SMEs such as the constraints on the firm's access to debt, SMEs valuation and financing activities, investment opportunities and profitability, and dividend payments.

My findings suggest that variables related to borrowing constraints, namely, capital intensity ratio (CI), cash holdings (Cash), tangible assets (TA), and S&P long term credit ratings (CRATING) play a significant role in the debt-free capital structure decisions of SMEs. Moreover, for the variables related to cash holdings, I find a negative relationship between debt-free SMEs and SMEs size with the level of cash holdings decreasing from micro to medium SMEs. This may be explained by the unstable financial nature of micro SMEs, which means that they need to keep higher levels of cash to face any sudden payments. Regarding the tangible assets variable, it is noted that within the debt SMEs, micro SMEs have the highest percentage of tangible assets compared to small and medium SMEs. This can be explained by the need of micro SMEs to mitigate their higher levels of cash flow uncertainty, moral hazard and adverse selection problems by providing higher levels of tangible assets as collateral for their debts. I also find that debt-free SMEs are significantly less likely to have a credit rating compared to debt SMEs; this implies that the debt-free SMEs' access to public markets is hugely restricted.

In addition I also find a significant effect of SMEs financing activities on the SMEs debt-free capital structure decisions using several proxies such as market to book ratio (MB), net debt issues (NDI), net equity issues (NEI), and changes in market equity (CME).

A surprising result is that a large number of debt-free SMEs pay significantly higher dividends than their debt SMEs counterparts. This might be due to the fact that dividend payments address shareholders' concerns about the agency problem, especially for large profitable debt-free SMEs, where dividends are used as a debt substitute to tackle the agency problem of high free cash flow. Furthermore, higher dividend payments can be seen as a way to enhance the ability of these highly debt-constrained SMEs to raise equity capital on more favourable terms without excessive adverse effects.

Finally, I find that pension obligations and lease commitments; do not play a significant role in explaining the debt-free policy. However, when conducting the logit regressions on entry and exit decisions of the debt-free SMEs I find that the NDTS plays a significant role in explaining the firm's decision whether to enter or exit the debt-free status.

My third empirical chapter builds on the analysis of the second chapter where I carry out the research on debt-free SMEs. In this chapter I am motivated by the increasing number of managerial decisions to follow a debt-free policy preferring to have no leverage compared to that which would maximize the firm value, even though it is argued, according to the capital structure hypotheses, that if firms deviate too far from their optimum leverage they will face higher probabilities of failure. Therefore, I attempt in this chapter to test the impact of the debt-free decision on the default risk of SMEs in the US market and how this substantial deviation from the optimal capital structure affects the SMEs' probabilities of failure compared to their leveraged counterparts. My methodological framework depends on forecasting the bankruptcy probabilities by developing two discrete-time duration-dependants hazard models for both groups under analysis, namely, debt and debt-free SMEs separately. To conduct the statistical analysis the Compustat database is used to construct my sample over the period from 1980 to 2013. The sample is limited to all available annual information extracted from Compustat for US SMEs. The final panel data sample employs annual firm-level data for (95,110) firm-year observations. This sample is divided into two main groups, namely, debt group containing (76,457) firm-year observations and debt-free groups containing (18,653) firm-year observations. Furthermore, within each group I classify SMEs into failed and non-failed SMEs. There are (309) firm-year observations within the debt-free group and (622) firm-year observations within the debt group. To validate the out-of-sample prediction performance of the models developed the entire study window is divided into two groups: the estimation period (1980-2008, 28 years) for the model building and the forecasting period (2009-2013, 5 years) for the out-of-sample forecasting performance test.

First of all, by reporting the frequency of failed and non-failed observations of SMEs for each of the debt and debt-free groups relative to the total number of observations in the sample in each year between 1980 and 2013, I find that the percentage of failed SMEs within the debt-free group is much higher than that of the debt group. One possible explanation for this difference is that, if the trade-off theory is correct, SMEs with a debt-free policy deviate substantially from the optimal capital structure which exposes them to higher probabilities of bankruptcy compared with debt SMEs.

Moreover, a general overview of the descriptive analysis for the covariates selected shows evidence of differences among the same variables in both SMEs' groups, which might be an indicator that the factors influencing failure probability differs between debt and debt-free group.

The final model for debt-free SMEs is estimated using eleven explanatory variables. The results show that all the selected covariates have their expected sign related to the default probability. However, I notice that R&D, WCTA, TA, WCSALE, and AS do not have statistically significant power in explaining the default probability of debt-free SMEs. As expected, tangible assets does not play a significant role in determining the probability of bankruptcy given that debt-free SMEs do not have a substantial amount compared to debt SMEs that rely substantially on tangible assets as collateral for obtaining external financing. On the other hand, I find that higher values of free cash flows and net investment opportunities significantly decrease the probability of failure for debt-free SMEs. Furthermore, the liquidity variable Cash is highly significant in my multivariate model, highlighting the importance of liquidity in the survival of debt-free SMEs.

On the other hand, the final model for debt SMEs is estimated using thirteen explanatory variables. The results show different determinants for the probability of bankruptcy that affect debt SMEs compared to those affecting the debt-free SMEs. For example, Tangible assets play a significant role in differentiating between the failed and non-failed debt SMEs. This is due to the importance of tangible assets in facilitating the access to external financing. Moreover, asset sales are found to significantly affect the probability of failure for debt SMEs, unlike the findings of those in debt-free SMEs. Furthermore, R&D expenses are found to significantly affect the failure probabilities of debt SMEs, with greater R&D expenditures increasing the survival probabilities of debt

SMEs. Both NDTS and NPL are found to positively affect the failure probabilities of debt SMEs, whereas OL5 fails to exhibit significant discriminatory power.

To summarise, a comparison of the default prediction models for debt and debt-free samples suggests that different sets of explanatory variables affect the default probabilities for these SMEs. My empirical findings clearly show that four explanatory variables, namely, RDR, TA, ABCE, and AS affect the probability of bankruptcy differently for each model, thus suggesting a potential need to treat debt and debt-free SMEs separately when modelling credit risk.

6.2. Implication of the Findings

The findings of this thesis are believed to have three main implications. The first implication is related to the development of the academic research area. The findings of third and fifth chapters are considered important for the further development of failure prediction models and credit risk management, while the findings of the fourth chapter provide further research on the capital structure literature. The second implication of the findings is their importance to lenders. While developing credit risk models for SMEs in the third and fifth chapter (taking into consideration the size segments and debt-free status) the findings provide important evidence suggesting that lenders have a separate credit risk modelling assessment for different size segments and treat debt and debt-free SMEs separately. These findings might enhance their risk management evaluation. The third implication of the findings is relevant for regulators. As SMEs play a vital role in the economy of each country, regulators aim to develop sound and healthy future regulation related to SMEs in order to enhance their functions and give better integration with the economy. The findings of this thesis provide further suggestions for the enhancement of the regulations related to SMEs. Regulators have to take into account the different features that exist within the SMEs sector especially the different size categories and the existence of debt-free SMEs when designing new regulations for SMEs.

6.3. Contributions

The results of the present study contribute to the existing literature about SMEs in several ways. Initially, in my first empirical chapter I contribute to the existing literature concerning SMEs bankruptcy risk by classifying the broad SMEs category into three main segments, namely, micro, small, and medium. This classification enables us to measure the effect of different size categories on the SMEs' probability of failure. My paper is a continuation and improvement of three papers in the literature of SMEs' failure: Altman and Sabato (2007), Holmes et al. (2010), and Gupta et al. (2014). I differ from Altman and Sabato's (2007) paper in two ways. Firstly, I further classify SMEs into three categories (micro, small, and medium) while modelling for bankruptcy prediction. In this study I capture differences existing between these categories and to what extent this finding might help lenders to further assess their credit models. Secondly, I utilize a more recent sample period (in and out of sample) which includes the recent financial crisis in 2007 to assess the extent to which the financial crisis affected the SMEs sector and the bankruptcy prediction model for SME firms. Holmes et al. (2010) study the survival of SMEs for the period from 1973 till 2001 and separate between micro firms and small and medium firms using hazard model methodology. They find that each segment is differently affected by firm-specific and macro-economic factors. However, the data used in their study differs from my data, as they concentrated their sample on a specific geographical location within the UK (North-East England) and they limited their sample to a specific industrial segment, the manufacturing sector, which represents only 12% of the UK firms. Moreover, they did not use any financial information in their analysis. In regard to Gupta et al.'s (2014) paper, I differ from it in several ways. First, I test the SMEs categories on a geographically different sample (US firms) and in doing so I emphasize the substantial soundness and significance of distinguishing between the broad SMEs categories. Second, from a methodological point of view, while applying discreet hazard models, the estimation of baseline hazard should be done using time dummies (Beck et al., 1998) or some other functional form of time (Jenkins, 2005). However, Gupta et al. (2014) created the baseline hazard including an insolvency risk variable, which distorts the idea of baseline hazard. Moreover, they utilized the ROC curve as their out of sample validation technique, although this technique has been criticized by many scholars who claim it generates misleading results. In my study, I have applied certain improvements to their paper by establishing a more precise baseline hazard function based on time dummies and applied an out of sample evaluation technique similar to the one used by Shumway (2001) which provides more accurate results.

My second empirical chapter contributes to the existing literature about SMEs capital structure. Even though a growing body of literature focuses on the capital structure of SMEs such as Berger and Udell (1998), Sogorb-Mira (2005), Matlay et al. (2006), and Ramalho and da Silva (2009), there is no study to my knowledge that has explored the zero-debt puzzle of SMEs. Therefore, in this study, I attempt to provide potential explanations for the reasons behind the choice of zero-debt along various dimensions and examine a number of economic mechanisms that I believe to further explain the phenomenon of extreme debt conservatism in SMEs.

My third empirical chapter contributes to the existing literature about SMEs bankruptcy by being the first empirical study investigating the effect of the debt-free decision on the default risk of SMEs in the US market and trying to answer how this substantial deviation from the optimal capital structure affects the SMEs' probabilities of failure compared to their leveraged counterparts. I address this issue by classifying my SMEs sample into two categories (Debt-Free and Debt) while modelling for bankruptcy prediction. Then I attempt to capture any differences, between these two models to identify the main determinants and to what extent they affect the failure probabilities for each of the studied groups.

A noteworthy contribution of the present thesis is that two empirical results on the SMEs probability of bankruptcy, out of three empirical studies, are obtained applying the discrete-time duration-dependant hazard model. By using this methodology, I am able to account for three serious econometric problems which static models such as multiple discriminant analysis and ordinary single-period logit techniques do not take into account in modelling default prediction due to the characteristics of bankruptcy data. These problems arise when investigating the effect of different SME size categories on the probability of failure and the effect of debt-free decisions on the SMEs' probability of failure; namely: (i) the inability of the static logit models to account for each firm's period at risk; (ii) the tendency of the single-period logit technique to lead to understated values of standard errors (Beck et al., 1998); (iii) the failure of static models to capture time-varying changes in the explanatory variable (Hillegeist et al., 2004).

6.4. Limitation

Despite the evidence documented in this thesis, the results of this study are subject to some caveats. Firstly, some researchers argue that including non-financial variables in the modelling of credit risk would provide better results and accuracy for the prediction models (see e.g. Altman et al. (2010)). Due to data limitation, the empirical results rely only on financial data extracted from Compustat. Even though the Compustat database provides some non-financial variables, however including these variables into the database would reduce the number of observations dramatically as many non-financial observations are not reported for SMEs in Compustat.

Moreover, a considerable number of SMEs are family owned firms and it is believed that the capital structure decision within the firm might be affected by this fact. Usually, founders might care more about the private benefits of control which is a well recognized dimension of agency cost. Due to data limitations, I had to limit this study by nott investigating the effect of family control on the capital structure decisions and assuming that capital structure decisions stem mainly from the firm's market and financial variables.

Furthermore, in the fourth chapter, I have tested the effect of credit rating as a signal for the firm's ability to access the debt market and use debt. Due to data limitation on Compustat, I have relied on the S&P rating which is provided in the database without including the ratings from other agencies such as Moody's and Fitch.

6.5. Future Research

The results of this thesis provide several avenues for future research. The first empirical chapter examines if any significant differences exist within the SMEs category in modelling for their probability of default using a certain number of financial explanatory variables. Different studies such as Altman et al. (2010) and Gupta et al. (2014) argue that including non-financial variables into the default probability models provide more information about the likelihood of default. Hence, I believe that this study can be further improved by the insertion of non-financial data such as owner characteristics, bank relationship history, auditing, etc. Moreover, I believe that it would be useful to conduct this study across different developed and emerging economies and compare the results with mine to highlight any differences that exist across economies.

The second empirical chapter on the main determinants of debt-free decisions can be further improved by testing the effect of family firms on the debt-free decisions. Previous studies such as Becker (1981) and Bertrand and Schoar (2006) argue that

CEOs of family firms could be particularly averse to risks posed by the presence of debt. Moreover, I believe that a likely explanation of the puzzling debt-free behaviour is in the preferences of corporate decision makers, managers, and large shareholders. A huge literature has been conducted on the effects of managerial preferences and corporate actions such as Lewellen (2006), Agrawal and Nagarajan (1990) and Malmendier et al. (2011). Therefore, an interesting avenue for future research is investigating the effect of CEO characteristics and corporate governance on the SMEs debt-free decisions. Furthermore, the unobserved heterogeneity in the structure of the investment process (e.g., front-loaded versus back-loaded) can influence the levels, timing, and persistence of corporate financial policy. Hence, I suggest carrying out further studies of endogenous dynamic relation between financing and investment that might affect corporate financial policies.

In my third empirical chapter I classify SMEs into debt and debt-free firms to capture any differences between these groups in modelling for default probabilities. However, taking into account the huge diversity that exists within the SMEs category (micro, small, and medium) in the form of access to external finance (Beck et al., 2006), capital structure (Ramalho and da Silva, 2009), default probability (El kalak and Hudson, 2015a), it would be interesting to extend this study by further dividing the SMEs according to their size into micro, small, and medium. This allows finding whether any difference exist in the default probabilities of debt and debt-free SMEs across the various size categories.

7. References

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