Corporate Credit Risk and Economic Performance

A thesis submitted for the Degree of Doctor of Philosophy

by

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February 2016

Abstract

This thesis is based on three essays in corporate credit risk and economic performance analysis.

Corporate bankruptcy prediction using past financial information is well established in the literature. Early studies of corporate bankruptcy prediction mainly applied statistical techniques such as discriminant analysis, logit and probit. Although, some of these models such as logit is still widely popular amongst the academics and practitioners due to its simplicity, the shortcomings of such models for bankruptcy prediction have been notified and criticised in the literature. One of the main shortcomings is that these models as linear classification approach can not explain the possible non-linear relationship between some accounting ratios and the probability of default (PD). This issue has been addressed in the literature by introducing non-linear statistical techniques such as support vector machines (SVM).

The first essay of this thesis, presented in Chapter 2, investigates the performance of SVM in corporate bankruptcy prediction and compares its performance with that of logit. This essay analyses bankruptcy risk for firms in the Asian and Pacific region using a list of financial ratios which covers different aspects of a firm's performance. The financial and credit event information for this analysis is provided by the Risk Management Institute of National University of Singapore (RMI NUS). With respect to forecasting accuracy, the findings of this analysis reveal that on average the SVM displays a higher forecasting accuracy and a more robust performance than the logit. Among several financial ratios suggested as predictors of default, leverage ratios and firm size display a higher discriminating power compared to others. Additionally, an analysis of the relationship between

PD and financial ratios is provided.

The accounting based models in bankruptcy analysis are mostly based on a set of measures which represents current financial position of the firms. However, these models have no indication of the status of the technology competency of a firm amongst its peers, which could be a more significant factor in the survival of a firm. Therefore, a new measure about level of firm's technological knowledge is required for a more precise assessment of firms future financial performance.

Considering the rise in the technological competition and patenting activities since the 1990s and also the important role of accurate credit rating modeling in the financial stability, second essay of this thesis examined in Chapter 3 focuses on the relationship between patent applications, as an output of a firm's technological development, and financial survival. Applying a survival analysis model, this relationship is empirically tested on a longitudinal firm-level data set for the listed firms in the US which matches the patent application data from European Patent Office (EPO) against a set of financial variables provided by RMI NUS. The results of this analysis reveal that patent applications are strong identifiers of low default risk companies.

In a further analysis, third essay of this thesis presented in Chapter 4 focuses on the impact of patent applications on firm's economic performance. In contrast to the studies which study the overall patent portfolio indicators as proxy for innovation, on a few aspects of firm performance this essay provides a comprehensive analysis of the effect of individual patent applications on several aspects of firm performance including including profitability, leverage, liquidity, size, credit rating quality and stock return. Using the matched data set of patent application data and economic variables for the US listed firms explained earlier, this essay examines whether changing from non-patenting to patenting status when a firm files its first and subsequent applications is associated with significant changes in its firm's performance and stability. The empirical findings of this essay indicates a higher capitalisation, increased liquidity, a lower leverage and an improve in credit quality for the patenting firms.

Dedicated to my parents

Acknowledgments

I am most grateful to my supervisor Dr. Russ Moro for his enormous and continuous help and valuable advices throughout my PhD study. Dr. Moro has always been the main resource for getting my research questions answered soon afterwards. All his valuable guidance and constant feedback was a great support to the quality and timely completion of this thesis. Dr. Moro has also been really understanding and supportive and has given me the chance to peruse various projects during my PhD without objections.

I owe my deepest gratitude to my parents who have sacrificed their lives for my sisters and myself and provided unconditional and continuous love and care. I would not have been able to make it this far without their support, patience and prayers. Words cannot express my sincere love, respect and appreciation to them. I would also like to thank my sisters, whom I dearly love, for their help and encouragements whenever I needed it.

I would also like to thank the academic staff at the Department of Economics and Finance in Brunel University London for their guidance and encouragement throughout my research. More specially, I am thankful to Professor Ashley Braganza, Head of the Department of Economics and Finance, Professor Menelaos Karanasos, Dr. Fabio Spagnolo, Dr. John Hunter and Dr. Faek Menla Ali for their kind support and valuable feedbacks at the PhD seminars.

My deepest appreciation goes to the Risk Management Institute (RMI) of the National University of Singapore (NUS) for providing financial support, data access and great research facilities for the study of corporate distress in Asia and the Pacific region, which forms the first essay of my PhD thesis. I would like to personally thank Professor Duan Jin-Chuan, former director of the RMI and

Dr. Oliver Chen former deputy director at RMI for their valuable suggestions and advices.

I am also thankful to Dr. Daniel Nepelski and Dr. Giuditta de Prato from the Institute for Prospective Technological Studies (IPTS) who provided data access and for their kind help and constructive comments that helped me to conduct second and third essays of my thesis.

My PhD thesis was hugely supported by the SAS Corporation in the UK, which provided me with a free SAS Student Fellowship license. This was a significant help towards the completion of my thesis. I really appreciate SAS Corporation for providing this facility.

Furthermore, I would like to thank all my friends who supported me during my PhD life with their kindness and incentivised me to strive towards my goals. My special thanks go to my lovely PhD colleagues, Mohammad Tajik, Thaana Ghalia, Nahla Samargandi and Husam Helmi. Thank you all for being so supportive in the tough times and also for giving me the opportunity to spend fun times and share beautiful memories with you.

Finally, I thank Professor John Hatgioannides (Cass Business School) and Professor Guglielmo Caporale (Brunel University London) for their valuable comments in the course of my PhD defence in December 2015.

Saeideh Aliakbari
February 2016

Declaration

I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree or award, other than that of the PhD, being studied at Brunel University London. I declare that all the material presented for examination is entirely the result of my own investigations except where otherwise identified by references and that I have not plagiarised anothers work.

The study presented in Chapter 2 of this thesis is a joint work with Dr. Russ Moro, Prof. Wolfgang Härdle and Linda Haffmann.

The analyses reported in Chapters 3 and 4 of this thesis are joint works with Dr. Russ Moro, Dr. Daniel Nepelski and Dr. Giuditta de Prato.

During my PhD, I have also worked on another research related to credit risk modeling "House Price and Credit Risk: Evidence from the United States" as a joint work with Dr. Mohammad Tajik and Thaana Ghalia which was published in the *Economic Modeling* journal in August 2015.

I also grant powers of discretion to the Librarian of Brunel University London to allow this thesis to be copied in whole or in part without the necessity to contact me for permission. This permission covers only single copies made for study purposes subject to the normal conditions of acknowledgment.

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Chapter 1

Introduction

In the last two decades of the 20th century the world witnessed several financial crises namely those concerning Latin American debt and US savings and loan in the 1980s, Asian currency in 1997 as well as the Nordic financial crisis in the early 1990s. These financial crises, usually became apparent with a number of defaults and bank failures which triggered further failures in the financial system. The instability in the financial system followed by a significant disruption of the economic activities and output eventually is seen as a major factor leading an economy into a great recession. Therefore, it is not surprising that these distressing events focused the minds of both researchers and financial regulators to understand causes and remedies of the financial crisis and provide more efficient supervisory and regulatory practices. Accordingly, risk management literature expanded to provide higher transparency and accuracy in risk assessment approaches which affect stability of the financial systems. The risk management literature mainly diverged in two different directions. One line of literature focused on determinants that undermine financial stability of firms (Becchetti and Sierra, 2003; Odders-White and Ready, 2006). Another line of risk management literature focused on the credibility of the statistical models applied by financial institutions and rating agencies to quantify counterparty risk (Carey and Hrycay, 2001; Altman and Saunders, 2001).

Recognising the importance of credit risk management in preventing financial crisis and mitigating their consequences, financial regulators proposed a set of measures called Base Capital Accord. This was a response to globalisation of financial markets and the increase of the role that financial markets played in the world economy. The first Capital Accord was introduced by the Basel Committee on Banking Supervision (BCBS) of the Bank for International Settlements (BIS) in 1988 and later adopted by major central banks by 1992. Basel I required banks to follow a more conservative approach primarily in relation to credit risk and the capital that they need to hold as a safeguard against the credit risk. In 2004, the BCBS introduced Basel II Capital Accord which was a further development of Basel I on the two main sources of financial risks i.e. credit risk and market risk. The main objectives of the Basel II were to ensure that firstly the capital requirements are more risk sensitive, secondly, that credit risk, market risk and operational risks are quantified appropriately and thirdly to introduce disclosure requirements enabling market participants to assess the capital adequacy of a financial institution.

Despite the developments in the literature and regulatory frameworks, world witnessed the global financial crisis in the late 2000s triggered by the US subprime mortgage crisis. Unlike the previous crises and mainly due to the notable globalisation of financial markets, the recent financial crisis rapidly spread amongst most advanced economies, the effects of which still partially linger. The global financial crisis resulted in several influential banking and corporate bankruptcies, a sharp reduction in asset prices and large losses in economic output in many countries around the world.

The recent financial crisis and its adverse consequences indicated a deficit in effectiveness of credit risk management and provisions of the previous regulatory frameworks. Implementing the Basel III Capital Accord in 2010 underlined an ongoing concern of the banking regulators and policy makers about adequate understanding of credit risk management in order to insure stable financial performance. Credit ratings in particular have gained importance because of their use in assessing banks' regulatory capital adequacy. Basel II allows banks to assess their credit risk and evaluate their capital requirements through internal credit ratings (see BCBS, 2003). Additionally, the role of an accurate credit assessment model has become more crucial with the rapid growth of the credit derivatives market in the last two decades. Finally, it has been conclusively demonstrated that the shortcomings of rating processes and models employed by rating agencies substantially contributed to the severity of the financial crisis. Therefore, addressing the issue of the accurate assessment of firms' credit risk and financial performance became a crucial element in safeguarding against credit risk which also helps to understand the determinants of the economic performance of banks, firms and economy as a whole (Hsu, 2009).

This thesis, therefore, aims to provide regulators and policy makers with more insight and transparency in the context of corporate bankruptcy modeling and financial performance analysis which has appeared crucial for the stability of the banking system, company survival and country's overall economic growth. It addresses the deficiencies in the corporates financial performance assessment both in terms of modeling and informative factors. Firstly, this study focuses on developing a corporate default prediction model with higher accuracy performance in various contexts compared to the commonly used models. Secondly, it bridges the existing informational inadequacies in the firms' credit and economic performance assessment. In particular, it analyses the significance of innovative and technological capabilities for firms' financial survival and economic performance.

In our research, we have been responding to the demand from industry, governmental organisations and the research community to provide an up-to-date methodology and a modeling paradigm for credit risk assessment and its determinants. We cooperated with and presented our conclusions and recommendations to the European Commission (EC) and Risk Management Institute of the National University of Singapore (RMI NUS) and received valuable input from these institutions as well as from the Deutsche Bundesbank.

This work would not have been possible without access to two unique data sources kindly offered to us by our partners. The first was a database complied and maintained by the RMI NUS, containing quarterly and annual company reports, default event indicators, industry information and stock prices for listed firms in US and the Asian - Pacific region as well as the macroeconomic data for the countries in which the firms operate. This data set was subsequently enriched with company information from other regions. The second database was built by the European Patent Office (EPO) and subsequently further enriched and provided by the Institute of Prospective Technological Studies (IPTS) of the European Commission (EC). These data contain priority patent application details submitted to 90 patent offices worldwide, providing a 98% coverage of all patent applications in the world. Access to global data allows tracking of all patent applications of companies submitted both nationally and internationally.

The comprehensive data access on the firm level allowed a distinctive analysis of firm bankruptcy and corporate performance beyond the coverage in the existing literature by (i) outlining the shortcomings of the widely used bankruptcy prediction models in terms of the prediction accuracy and hence suggesting an alternative approach; (ii) analyzing firms financial stability in the Asian and Pacific region and allowing a comparison with other regions such as Europe; (iii) providing an understanding of the role of non-accounting measures in combination with accounting and stock performance indicators for firms' financial stability and economic performance.

Details and more background to the empirical investigations presented in the subsequent chapters are as follows:

Chapter 2 of this thesis investigates the performance of a corporate default prediction model built upon the most significant accounting determinants of bankruptcy for the companies in the Asia and Pacific region. The objective of this chapter is to propose a rating model which overcomes shortcomings associated with the most commonly used models in terms of their credibility and accuracy performance.

The traditional default analysis models which since the 1960s focused on the statistical analysis of financial ratios was later augmented with the stock market performance measures all of which displayed predominance of the traditional models and input. A vast majority of these models are based on a linear combination of accounting performance measures, which often have insufficient granularity and discriminatory power when applied to a large data set that can contain millions of observations. Investigation into models displaying additional statistical features such as non-linearity or an ability to deal with multiple input simultaneously has not been sufficiently undertaken in the literature and this is the gap we intend to address in Chapter 2.

A collection of models based on statistical learning theory (Vapnik, 1998) commonly referred to as support vector machine (SVM) is of particular interest due to their advantages, among others, of an ability to map non-linear multivariate dependencies and a good generalisation ability leading to a high out-of-sample forecasting accuracy.

Chapter 2 of this thesis extends the current literature in bankruptcy analysis by examining performance of SVM and comparing its accuracy to that of logistic regression for firms in the Asian and Pacific region. The model considers a wide range of financial ratios which reflects firm's profitability, leverage, liquidity, activity, cost structure and dynamic position and also its size. The results of this analysis firstly confirm a non-linear relationship between some financial ratios such as leverage and sales with probability of default (PD) which further questions credibility of linear regression analysis for bankruptcy prediction. Secondly, as expected, it shows that an SVM with a high generalisation ability is a promising method for distress forecasting in the Asian and Pacific region and provides a reduction of model risk and a more robust performance compared to the Logit. Similar findings on the advantages of SVM compared to Logit have been reported by Lacerda and Moro (2008) and Dellepiane et al. (2015) who performed analyses of European based firms. This validates the applicability of non-linear techniques such as SVM in corporate distress analysis in different regions.

In Chapter 3 we further explore the topic of the determinants of corporate distress and focus our attention on the non-tangible assets such as technological expertise and innovation.

Relying only on accounting information in bankruptcy analysis could be questionable when for example low return firms are classified as distressed with higher risk. These firms with low current returns display high sales growth and R&D expenses. In the absence of an accounting policy which allows capitalising R&D expenses, the firms, nevertheless, have to fully expense their R&D spending. This results in lower net income and deteriorating accounting performance which is even more evident in R&D intensive industries. Therefore, accounting based models in distress forecasting have become less conclusive especially due to the rising significance of R&D and an increasing likelihood of distress misclassification (Franzen et al., 2007). This means that in order to have a more efficient assessment of firms future financial stability, a new measurement which captures the level of technological knowledge and competition capabilities is needed especially for technology intensive firms. In order to bridge such informational deficit in credit rating and firm performance analysis, various proxies of R&D output and innovative activities can be considered to facilitate detailed analysis of specific technological aspects (Ernst, 2003).

In this regard, the explicit and implicit importance of a patent, as an output of R&D activities in firms' bankruptcy and performance analysis, is justified for several reasons. First, patents are an indication of realised technologies influencing future operating performance and protecting higher income. Second, patents are a measure of competition because they are exclusive to the business (Eisdorfer and Hsu, 2011). Third, patents can generate licensing income or they can be traded with other firms through cross-licensing. Fourth, patents can be used to expand market power internationally and enhance the firm's reputation (Neuhäusler, 2012).

Most of the existing studies examining the link between patent and bankruptcy consider patent portfolio indicators such as patent flow and patent citations (Neuhäusler et al., 2011), number of patent applications and patent issues in a year (Hsu, 2009). Chapter 3 of this thesis complements the existing literature in several ways. It investigates the significance of so called priority patent applications on corporate default. Where patent application processing usually takes up to three years to be assessed, granted and often start generating income, the information about patent application is disclosed to the public after 18 months of the priority date of the application. Therefore, priority patent applications can be an early indicator of future income for forward looking analysis (Ernst, 2001). We apply a Cox (1972) proportional hazard (PH) survival model, which constitutes the current state of the art in corporate credit rating modeling. Survival analysis takes into consideration the most recent information and also provides information on the predicted distribution of the time to default. Additionally, we include market-based variables in combination with accounting variables in the context of credit rating which is motivated by two previous studies by Shumway (2001) and Franzen et al. (2007) questioning the significance and effectiveness of most of the previously used accounting information in bankruptcy analysis. The results of our study reveal the fact that innovation activities are strong identifiers of credit default risk.

Chapter 4 of this thesis expands the scope of the investigation of the impact of innovation on credit default risk by comprehensively examining the effects on a range of company performance characteristics, such as profitability, capital structure, stock market performance and growth. The majority of existing studies in corporate finance literature are limited to analysing the impact of R&D as an indicator of innovative activities of firms on just one performance indicator. Due to the nature of of R&D projects, their outcomes are associated with a high risk of failure and even if the R&D projects are successful, there is a long delay between R&D investment and establishing their outcomes in the market. Also, imitation and spill over effects to other firms traditionally associated with R&D most likely reduce profitability.

In our study by analysing several channels of impact simultaneously we are able to obtain a comprehensive picture of how innovation affects company performance. To complement the previous studies which mainly consider the analysis of patent portfolios, Chapter 4 of this thesis focuses on the impact of individual priority patent applications on firms economic performance. This allows us to examine the earliest recorded manifestation of innovation even if it did not result in granting a patent. We can also answer important questions about the value of individual patents and their effect in terms of profitability, capital appreciation, credit rating, liquidity, stock prices and external and internal financing.

This chapter contribute to the existing literature in several ways. Firstly, it provides a detailed analysis of economic performance of patenting versus non-patenting firms. Secondly, it investigates whether the differences between performance of patenting and non-patenting firms reflect actual changes following patenting or if they are simply due to self-selection of larger, more profitable and productive firms opting for patenting for various reasons. While the economic performance of firms three years before filing a patent is controlled, the impact of patent applications is tested on the difference between the after-patenting and past performance. The empirical findings of this chapter suggest higher capitalisation, increased liquidity, a lower leverage and higher stock return for patenting firms.

Chapter 5 of this thesis provides a summary of the main conclusions of this thesis along with some recommendation for policy implications. It also draws attention to the main limitations of this thesis and makes suggestions for further research.

Chapter 2

Forecasting Corporate Distress in the Asian and Pacific Region

2.1 Introduction

Although credit risk has always been a major concern for investors, in recent years high profile insolvencies have attracted widespread attention, first, after the dot-com bubble and then in connection with the subprime mortgage crisis. In the Asian and Pacific region, a wave of insolvencies were caused by the crisis of 1998. The announcement of the Basel III Capital Accord in 2010 after the adoption of Basel II in 2004 and Basel I in 1992 indicates the concern of both banks and regulators in terms of providing protection against credit risk and, at the same time, inadequacy of the existing protection measures and methods for measuring risk.

As early as the beginning of the twentieth century Winakor and Smith (1935) proposed the use of financial ratios for separating firms into solid stable and potentially bankrupt ones. Foster and Ramser (1931) and Fitzpatrick (1932) also applied financial ratios for bankruptcy prediction. The systematic application of statistics for bankruptcy analysis started with the work of Beaver (1966) and Altman (1968) introducing the univariate and multivariate discriminant analysis (DA), respectively. Altman (1968) established a formula for predicting bankruptcy which is a linear combination of five financial ratios known also as the linear Z-score model (Altman et al., 1977). This model remains popular for forecasting default rates even today due to its simplicity. The drawback of the Z-score model is the unlikely assumption of equal normal distributions for both failing and solvent firms with the same covariance matrix.

Later the focus of research shifted towards the Logit and probit models (see for instance Ohlson, 1980; Martin, 1977; Wiginton, 1980; Zavgren, 1983; Zmijewski, 1984). The Logit models depend upon less restrictive statistical assumptions and also offer better performance (Zavgren, 1983). Logit model is widely used by academic and practitioners. One of the attractive features of Logit is that its score is calibrated as default probability, whereas in many other models such as DA the score has to be converted to default probability.

Other statistical methods which were introduced at the same time, such as the gambler's ruin model (Wilcox, 1971) and option pricing theory (Merton, 1974), were based on time series data. Later, hazard or survival models (Shumway, 2001; Glennon and Nigro, 2005) and the Forward Intensity Approach (Duan et al., 2012) used both time series and cross-sectional data. Other types of models such as recursive partitioning (Frydman et al., 1985) and rough sets (Dimitras et al., 1999) were mostly applied to cross-sectional data.

One of the major shortcomings of many methodologies is the fact that they ignore the possible non-monotonic relationship between some financial ratios and the probability of default (PD) such as the logistic regression (see for example Falkenstein et al., 2000; Manning, 2004; Fernandes, 2005; Chen et al., 2011). For instance, PD is non-monotonically dependent from the net income (NI) growth. Negative or very slowly growing NI may create difficulties for company to pay its debt obligations when they fall due. On the other hand, high NI is likely to be non-sustainable in the long term causing high volatility. Both situations can lead to a higher PD, which is in accordance with the existing literature (e.g. Merton, 1974; Bharath and Shumway, 2008). The identification of the shape of the dependence, however, still remains a problem.

Another problem is the potential error associated with identification of the dependency between financial ratios and the default probability, even if the relationship is known to be monotonic. For example, in logit, a logistic transformation of financial ratios is applied which might not be the correct dependency (Lacerda and Moro, 2008).

The non-linear dependence between some financial ratios and the PD has been addressed by applying non-linear models such as artificial intelligence (Bryant, 1997) and machine learning techniques such as recursive partitioning, also known as classification and regression trees (Frydman et al., 1985), proximal support vector machines (PSVM) (Friedman, 2002), support vector machines (SVM) (Martens et al., 2006; Chen et al., 2011) and artificial neural networks (ANNs) (see for instance Elmer and Borowski, 1988; Markham and Ragsdale, 1995; Malhotra and Malhotra, 2002). In particular, ANNs compared to other classifications techniques, have been reported with higher classification accuracy in several studies (Kim and Sohn, 2010). However, Kim and Sohn (2010) lists some shortcomings for ANN. First, ANN involves the researchers's experience and knowledge of data preprocessing for selecting control parameters. Second, it is hard to generalise the results of ANN due to overfitting. Third, explaining the prediction results is difficult for ANN due to its lack of explanatory power.

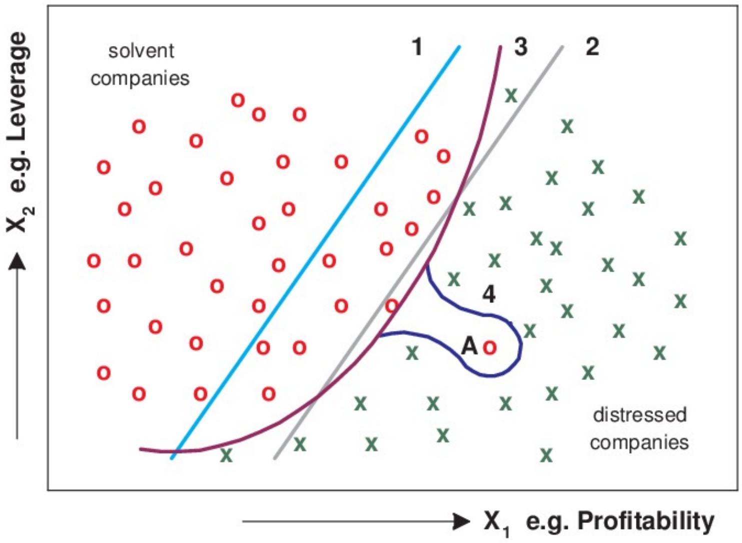
In contrast, among the non-linear classification techniques, SVM which was developed by Vapnik (1998) overcomes the above shortcomings. SVM is a classification method based on statistical learning theory (Vapnik, 1995, 1998). SVM produces a binary classifier , so called "optimal separating hyperplanes" or "maximum margin hyperplane" by transforming the input vectors into the high dimensional space. The maximum margin hyperplane provides the maximum separation between the classes. SVM constructs a linear model to estimate decision function using non-linear class boundaries based on support vectors which are the training observations closest to the maximum margin hyperplane. This is done by a kernel function which can have different forms such as polynomial kernel and the Gaussian radial basis function.

Shin et al. (2005) lists some advantages of using SVM: (i) only two parameters need to be chosen, the upper bound and the kernel parameter, (ii) as the training of SVM is done through solving a linearly constrained quadratic problem, the solution of optimal and global is unique, (iii) SVM employs the structural risk minimization principle that minimizes an upper boundary on the actual risk, in contrast to empirical risk minimisation which minimises the error based on the training data set, hence SVM is equipped with greater generalization ability.

When classifying distressed vs. solvent companies, the SVM allows adjustment of its complexity. The complexity can be then optimised with respect to some accuracy measure, for example the accuracy ratio (AR), for the data and predicting variables at hand. Figure 2.1 illustrates the classical trade-off between the good in-sample performance and the generalisation ability. In this example by changing complexity of the classification method with respect to some accuracy criterion, it is possible to establish an optimal boundary.

In this chapter, a bankruptcy prediction model for firms in the Asian and Pacific region using SVM is built considering a wide range of financial ratios which reflects firms profitability, leverage, liquidity, activity, cost structure and dynamic position and also firm's size. In order to evaluate the prediction power of SVM, a

Figure 2.1: A classification example.



Note: The boundary between the classes of solvent and insolvent companies can be either linear (1 or 2) or non-linear (3 and 4). A model capable of producing non-linear boundaries can have low (linear cases 1 and 2), moderate (case 3) and high (case 4 where overfitting is evident) complexities. By optimising the complexity with respect to some accuracy criterion, the optimal boundary can be established (e.g. case 3).

comparison between SVM's prediction accuracy with that of logistic regression is provided.

The organization of this chapter is as follows. Section 2.2 describes the data set and the financial variables used to construct a bankruptcy prediction model with SVM. In 2.3, the details of SVM model for bankruptcy prediction are explained. Section 2.4 conducts an empirical data analysis. Finally, Section 2.5 concludes.

2.2 Data Description

The data used in this chapter were collected and prepared by the Risk Management Institute (RMI) of the National University of Singapore (NUS). The data contain quarterly and annual company reports, default indicators and stock prices for $25,000$ listed firms from the Asian and Pacific region as well as the macroeconomic and selected financial data for the countries in which the firms operate. The time coverage spans from 1980 to 2010. The database also indicates the relevant industry of operation for each firm. In this analysis companies in the financial sector, asset backed securities, funds and government owned enterprises are excluded since the nature of these businesses is different from non-governmental manufacturing firms and service providers.

At the first stage the financial data are converted into financial ratios. These ratios are grouped into seven categories: profitability, leverage, liquidity, activity, cost structure, dynamics and size, characterising company performance from different sides.

Financial reports in the database are released quarterly, semi annually and annually, however, the beginning of a financial year and, hence, reporting dates for companies are different and spread throughout the year. To reflect this situation each financial report is indexed by a unique time ID number according to the year and month of the report in order to have the financial information on a regular monthly basis for all firms. Since the reporting date almost invariably falls on the last day of a month, this encoding gives the precise time of a default event.

After assigning the report time ID number to each observation, distressed firms are defined based on the default information in the database. Each monthly report of a firm receives the default indicator $y = 1$ if the firm files a credit event report within a one year long period starting after one year of the date of the financial report (distressed observations). For the rest of the observations (solvent observations) the default indicator is $y = -1$. In this chapter this horizon is called specification *design 1*. This horizon is considered in order to analyse the effects of the default on the long term debt which has maturity of over one year.

Additionally, to see the effects of the short term debt on PD, distress for a

Table 2.1: Distribution of distressed and solvent firms for each country.

Country	Horizon: *Design 1* Distressed firms	Horizon: *Design 1* Solvent firms	Horizon: *Design 2* Distressed firms	Horizon: *Design 2* Solvent firms
Australia	3 (2.01 %)	146	6 (4.03 %)	143
China	1088 (2.42 %)	43784	4182 (7.22 %)	53739
Hong Kong	10 (0.18 %)	5514	19 (0.34 %)	5505
India	48 (0.17 %)	28840	148 (0.51 %)	28775
Indonesia	26 (0.42 %)	6131	70 (1.12 %)	6186
Japan	124 (0.17 %)	71489	258 (0.36 %)	71380
Malaysia	385 (1.17 %)	32512	1100 (3.12 %)	34173
Philippines	113 (1.90 %)	5839	267 (4.16 %)	6154
Singapore	34 (0.48 %)	7009	77 (1.08 %)	7050
South Korea	99 (0.20 %)	49828	232 (0.46 %)	50153
Taiwan	260 (1.08 %)	23906	604 (2.47 %)	23809
Thailand	202 (1.19 %)	16702	486 (2.77 %)	17028

different horizon is analysed. For this purpose, the default indicator $y = 1$ is assigned to those observations recording a credit event report filing within the two year period from the date of the financial report (distressed observations) and for the rest (solvent observations) the default indicator is $y = -1$. This horizon specification is called *design 2*.

A broad range of credit events is applied to identify distressed firms and assign the default indicator ($y = 1$), including filings under Chapter 11, Chapter 15, Chapter 7, restructuring, liquidation, being sued by creditors and failing in coupon and principle payments.

In the data set with the horizon under the *design 2* specification, there are 311,682 observations from which 7,449 (2.39%) observations are indicated as distressed and 304,233 (97.61%) as solvent. The distribution of solvent and distressed observations among countries varies substantially. For instance, for Australia and Hong Kong, there are respectively only 6 (4.03%) and 19 (0.34%) of distressed observations out of 149 and 5,524 observations whereas for China there are 4,182 (7.22%) distressed observations out of 57,921 observations (see Table 2.1).

2.2.1 Variable Description

The components of the financial ratios which are estimated from data are explained in Table 2.2 and the summary statistics for them for distressed and solvent firms are provided in Tables 2.3 and 2.4.

The variables are grouped in to seven broad categories: profitability, leverage, liquidity, activity, cost structure, dynamic and size. These variables have been widely used in the prior literature of corporate bankruptcy. In these studies, profitability ratios have been shown to be strong predictors of distress. For example NI/TA is an indication to investors about how effectively the firm is using its assets to generate profit. Higher NI/TA essentially means that the firm is generating more income on less investments.

Leverage ratios are also important measures of financial distress. As it can be expected, firms with higher debt leverage are more likely to face financial difficulties when their debt falls due.

Liquidity as a common indicator in credit risk assessment, represents the firms' ability to quickly convert its assets into cash. CASH/TA is one of the main liquidity ratios used in the literature which has appeared with a highly significant power in bankruptcy prediction. The larger CASH/TA the better the position of the firm.

Activity ratios also reveal important information in credit default estimation. For instance INV/S which is the inventory turnover indicates the number of time that a firm's inventory has been sold and replaced. High INV/S implies poor sale and excess inventory which is an indication of existing investments with zero rate of return, hence unhealthy financial position.

Among the cost structure ratios, EBIT/INT paid is one of the most predictive variables (Falkenstein et al., 2000) which determines how easily a firm's earning can cover the outstanding interest payments.

Dynamic ratios, such as NI-Growth could potentially have both positive or negative relationship with PD (e.g. Merton, 1974; Bharath and Shumway, 2008). Negative or very steady NI-Growth may create strains for company to pay its debt payments when they fall due. On the other hand, high NI-Growth might not be sustainable in the long term resulting in high volatility. Both situations can increase PD.

Firms's size indicators such as Log(TA) has also been considered in the literature of corporate bankruptcy which allows to consider the default risk assessment between small, medium and large firms. Access to capital for small and medium size firms is different which can affect the prediction power of some other financial variables and hence the predictability power of the model (Chen et al., 2011).

The prior empirical studies have found that the probability of default is higher if a firm is not profitable, highly leveraged and face cashflow restraints. Moreover, larger firms are less likely to face financial distress due to their reputation and better access to credit market (see for instance Myers, 1977; Aghion and Bolton, 1992; Shumway, 2001; Bonfim, 2009; Duan et al., 2012; Modina and Pietrovito, 2014).

Table 2.2: Variable Description

Variable	Description
	Profitability
NI/TA	Return on assets: net income / total assets
NI/S	Net profit margin: net income / sales
OI/TA	Operating return on assets: operating income / total assets
OI/S	Operating profit margin: operating income / sales
EBIT/TA	Earnings before interest and taxes / total assets
EBIT/S	Earnings before interest and taxes / sales
	Leverage
OK/TA	Own capital ratio: own capital / total assets
CL/TA	Current debt ratio: current liabilities / total assets
TD/TA	Bank debt ratio: total bank debt / total assets
	Liquidity
STD/D	Fraction of debt which is short term debt
CASH/TA	Cash and cash equivalents / total assets
CASH/CL	Cash ratio: cash and cash equivalents / current liabilities
QA/CL	Quick ratio: quick assets / current liabilities
CA/CL	Current ratio: current assets / current liabilities
WC/TA	Current assets - current liabilities / total assets
CL/TL	Current liabilities / total liabilities
	Activity
TA/S	Asset turnover: total assets / sales
INV/S	Inventory turnover: inventories / sales
AR/S	Account receivable turnover: account receivables / sales
AP/CS	Account payable turnover: account payables / cost of sales
	Cost Structure
INT/D	Average cost of debt: interest payments / debt
EBIT/INT paid	Interest coverage ratio: earnings before interest and taxes to interest paid
	Dynamic
Sales-Growth	One year growth in sales
NI-Growth	One year growth in income
	Size
Log(TA)	Logarithm of total assets
Log(S)	Logarithm of total sales

2.2.2 Summary Statistics

In this section summary statistics of the financial ratios for distressed and solvent companies are provided. They are reported for *Design 1* (Table 2.3) and *Design 2* (Table 2.4) horizons, pooled across countries and years. The first five columns in each table summarize the estimates for distressed companies and the next five columns report the estimates for solvent companies. $q_{0.05}$ and $q_{0.95}$ are 5% and 95% quantiles. N is the number of observations for which the ratio can be computed based on the available data and IQR represents the interquartile range for each ratio.

As it is evident in both tables, a brief analysis confirms that on average: (i) distressed firms are less profitable than the solvent firms, (ii) the liquidity ratios are favorable to solvent firms, (iii) activity indices, i.e. TA/S and INV/S, indicate higher turnover for solvent firms, (iv) the leverage ratios reveal greater solvency for the solvent firms, (v) solvent firms have significantly higher EBIT to interest charges, (vi) dynamic indicators exhibit an interesting behavior which is higher Sales-Growth and lower NI-Growth for solvent firms, (vii) distressed firms are smaller than solvent firms and show weaker sales revenue. Overall, These findings are consistent to what has been usually documented in the literature (see for instance Ohlson, 1980; Campbell et al., 2008; Bonfim, 2009; Modina and Pietrovito, 2014).

Tables 2.4 also show that the lowest number of available observations belong to 4 variables: INT/D, EBIT/INT, AP/CS and STD/D. Table 2.5 presents the distribution of distressed and solvent firms after removing these 4 variables with most missing values. After removing them and cleaning missing values the total number of distressed observations in the data set increases from 1,182 to 4,683 in design 2.

Table 2.3: Summary statistics for distressed and solvent firms across countries and years. Bankruptcy horizon: *Design 1.*

1986-2010	Distressed Firms					Solvent Firms				
Variable	N	$q_{0.05}$	Med	IQR	$q_{0.95}$	N	$q_{0.05}$	Med	IQR	$q_{0.95}$
					Profitability					
NI/TA	1529	-0.10	-0.00	0.01	0.04	231456	-0.05	0.01	0.02	0.05
NI/S	2062	-2.90	-0.00	0.05	0.30	281329	-0.57	0.03	0.09	0.27
OI/TA	1704	-0.06	0.00	0.01	0.03	232939	-0.03	0.01	0.02	0.05
OI/S	1723	-1.17	0.02	0.09	0.30	249187	-0.37	0.05	0.11	0.29
EBIT/TA	1523	-0.06	0.00	0.01	0.04	231084	-0.03	0.01	0.02	0.05
EBIT/S	1542	-1.41	0.02	0.10	0.31	247091	-0.37	0.05	0.11	0.29
					Leverage					
OK/TA	1716	-0.68	0.36	0.49	0.67	234206	0.16	0.54	0.70	0.88
CL/TA	1716	0.15	0.48	0.65	1.51	233974	0.07	0.32	0.45	0.68
TD/TA	1506	0.12	0.44	0.58	0.87	228469	0.00	0.20	0.36	0.58
					Liquidity					
STD/D	1497	0.12	0.80	0.97	1.00	204949	0.08	0.69	0.97	1.00
CASH/TA	1685	0.00	0.04	0.10	0.27	233234	0.00	0.09	0.17	0.38
CASH/CL	1685	0.00	0.08	0.24	0.84	232945	0.01	0.27	0.65	2.70
QA/CL	1680	0.11	0.68	1.08	2.15	231103	0.30	1.11	1.91	5.58
CA/CL	1713	0.18	1.00	1.47	2.79	233920	0.50	1.52	2.46	6.60
WC/TA	1713	-0.96	-0.00	0.17	0.42	233948	-0.22	0.17	0.34	0.58
CL/TL	1716	0.28	0.81	0.95	1.00	233921	0.32	0.78	0.92	1.00
					Activity					
TA/S	1697	2.29	8.67	16.61	90.13	232584	1.74	4.69	7.59	22.83
INV/S	1657	0.05	0.80	1.62	8.57	229603	0.01	0.47	0.84	2.26
AR/S	1653	0.17	0.93	1.66	4.82	230847	0.08	0.72	1.07	2.05
AP/CS	1085	0.09	0.65	1.14	4.52	174888	0.04	0.41	0.68	1.33
					Cost Structure					
INT/D	712	0.01	0.03	0.08	0.70	130408	0.00	0.02	0.06	0.56
EBIT/INT paid	803	-20.08	0.45	2.68	20.53	172564	-28.08	4.25	19.86	326.33
					Dynamics					
Sales-Growth	1617	-72.55	-2.81	27.42	119.62	226216	-48.84	5.21	23.89	97.17
NI-Growth	1744	-5.59	0.46	1.26	13.34	229415	-4.69	0.18	0.93	5.14
					Size					
log(TA)	1721	4.73	7.57	9.12	12.21	234284	4.95	9.31	11.02	13.51
log(S)	2249	1.80	4.94	6.45	9.83	284275	2.32	7.09	9.24	11.85

Note: The left five columns represent distressed firms and the right five columns represents solvent firms. N indicates the number of observations which contain the variable. $q_{0.05}$ and $q_{0.95}$ are respectively 5% and 95% quantiles. IQR is the interquartile range.

Table 2.4: Summary statistics for distressed and solvent firms across countries and years. Bankruptcy horizon: *Design 2*.

1986-2010	Distressed Firms					Solvent Firms				
Variable	N	$q_{0.05}$	Med	IQR	$q_{0.95}$	N	$q_{0.05}$	Med	IQR	$q_{0.95}$
Profitability										
NI/TA	4989	-0.15	-0.00	0.00	0.03	240454	-0.06	0.01	0.02	0.05
NI/S	6657	-4.18	-0.03	0.04	0.26	292615	-0.69	0.03	0.09	0.28
OI/TA	5342	-0.09	0.00	0.01	0.03	241847	-0.04	0.01	0.02	0.05
OI/S	5397	-1.81	0.01	0.08	0.29	257567	-0.44	0.05	0.11	0.29
EBIT/TA	4967	-0.09	0.00	0.01	0.03	240011	-0.04	0.01	0.02	0.05
EBIT/S	5022	-2.12	0.00	0.09	0.30	255490	-0.43	0.05	0.11	0.29
Leverage										
OK/TA	5381	-1.25	0.34	0.48	0.63	243232	0.12	0.53	0.70	0.88
CL/TA	5381	0.18	0.54	0.72	2.02	242997	0.08	0.32	0.47	0.73
TD/TA	4913	0.15	0.44	0.58	1.06	237398	0.00	0.21	0.37	0.60
Liquidity										
STD/D	4890	0.17	0.89	1.00	1.00	213146	0.08	0.71	0.97	1.00
CASH/TA	5296	0.00	0.05	0.11	0.30	242186	0.00	0.08	0.17	0.38
CASH/CL	5296	0.00	0.08	0.24	0.71	241890	0.01	0.26	0.63	2.63
QA/CL	5289	0.10	0.64	1.00	1.91	239845	0.27	1.09	1.87	5.47
CA/CL	5375	0.15	0.90	1.37	2.40	242893	0.44	1.49	2.41	6.51
WC/TA	5375	-1.67	-0.04	0.16	0.37	242925	-0.29	0.16	0.33	0.58
CL/TL	5381	0.33	0.88	0.97	1.00	242941	0.32	0.79	0.93	1.00
Activity										
TA/S	5294	2.53	9.79	17.62	107.11	240836	1.75	4.77	7.89	25.78
INV/S	5193	0.09	0.90	1.78	9.48	237729	0.01	0.48	0.87	2.54
AR/S	5185	0.19	1.00	1.82	6.54	238940	0.08	0.72	1.09	2.18
AP/CS	3427	0.08	0.65	1.20	4.97	178398	0.04	0.42	0.69	1.38
Cost Structure										
INT/D	1802	0.01	0.04	0.12	3.02	131670	0.00	0.02	0.06	0.57
EBIT/INT paid	2095	-22.50	-0.38	1.68	12.90	174050	-28.00	4.18	19.60	322.00
Dynamics										
Sales-Growth	5389	-78.25	-7.82	20.61	117.90	235485	-51.28	5.12	24.24	100.80
NI-Growth	5792	-6.71	0.48	1.43	19.97	239939	-4.77	0.19	0.94	5.31
Size										
log(TA)	5393	4.70	7.31	8.32	11.49	243336	4.89	9.16	10.97	13.46
log(S)	7029	1.39	4.70	5.94	9.39	295454	2.18	6.93	9.17	11.80

Note: The left five columns represent distressed firms and the right five columns represents solvent firms. N indicates the number of observations which contain the variable. $q_{0.05}$ and $q_{0.95}$ are respectively 5% and 95% quantiles. IQR is the interquartile range.

Table 2.5: Distribution of distressed and solvent firms across countries.

Country	Horizon: *Design 1* Distressed firms	Horizon: *Design 1* Solvent firms	Horizon: *Design 2* Distressed firms	Horizon: *Design 2* Solvent firms
Australia	0 (0.00 %)	48	0 (0.00 %)	48
China	634 (1.83 %)	34048	2639 (6.10 %)	40627
Hong Kong	3 (0.19 %)	1588	7 (0.44 %)	1584
India	0 (0.00 %)	156	0 (0.00 %)	156
Indonesia	26 (0.45 %)	5758	70 (1.19 %)	5811
Japan	104 (0.16 %)	64735	227 (0.35 %)	64637
Malaysia	274 (1.14 %)	23693	813 (3.21 %)	24512
Philippines	39 (2.04 %)	1870	102 (4.84 %)	2007
Singapore	29 (0.53 %)	5431	70 (1.27 %)	5454
South Korea	77 (0.16 %)	48115	177 (0.37 %)	48385
Taiwan	77 (0.35 %)	22025	226 (1.02 %)	21947
Thailand	161 (1.07 %)	14856	352 (2.27 %)	15124

Note: The distribution represents the data set after removing 6 variables with most missing values. These variables are: INT/D, EBIT/INT, AP/CS, STD/D, Sales-Growth and NI-Growth.

2.3 Methodology

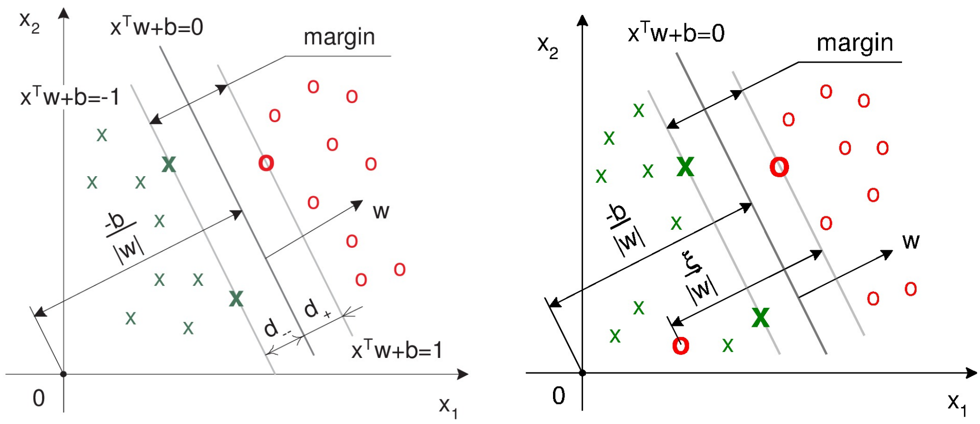
The support vector machine (SVM) applied in this chapter is a statistical method for binary classification that is a practical implementation of the Tikhonov regularisation principle (Tikhonov, 1963; Tikhonov and Arsenin, 1977). It is based on linear classifiers that simultaneously maximise the margin or the distance between the classes and minimise empirical risk related to misclassifications on a given data set Vapnik (1995).

Figure 2.2 illustrates the maximum margin classification for linearly separable and non-separable data in a two-dimensional case. The separating function generated by a linear SVM is

$$x_i^\top w + b = 0 \tag{2.3.1}$$

Such a classification rule makes an SVM similar to logit. x_i is a $d \times 1$ vector of the characteristics of firm i, e.g. financial ratios described in Appendix B, whereas d is the number of characteristics or variables used. w is a $d \times 1$ vector of weights

Figure 2.2: The separating hyperplane $x^\top w + b = 0$ and the margin in a linearly separable (left) and non-separable (right) case.



Note: Crosses denote solvent companies, zeros are the insolvent ones. The hyperplanes bounding the margin zone equidistant from the separating hyperplane are represented as $x^\top w + b = 1$ and $x^\top w + b = -1$. The misclassification penalty in the non-separable case is proportional to the distance $\xi / \|w\|$.

which determine the slope of the separating function. The scalar b is a location parameter or a threshold.

The margin is the empirically estimated distance between the opposite classes of observations. In Figure 2.2 it is shown as the distance between the margin boundaries – the parallel lines located symmetrically on both sides of the separating function. In a perfectly separable case such as in Figure 2.2, left panel, no observations may lie in the margin zone and all observations must satisfy the constraints:

$$x_i^\top w + b \geq 1 \quad \text{for} \quad y_i = 1, \tag{2.3.2}$$
$$x_i^\top w + b \leq -1 \quad \text{for} \quad y_i = -1 \tag{2.3.3}$$

The constraints ensure that the observations of the opposite classes lie on the opposite sides from the margin gap.

Misclassifications may occur if data are linearly non-separable as in Figure 2.2, right panel. Here the bold zero on the left-hand side of the separating line shows a solvent company that is classified as insolvent. SVM adjusts the weights w and the location parameter b in such a way that the margin is maximised and the sum of misclassification errors ξ_i is minimised. $\xi_i \geq 0$ is also called a slack variable and is introduced to (2.3.2) and (2.3.3) to ensure that these constraints are satisfied. For any observation x_i the modified constraints must hold:

$$
\begin{aligned}
x_i^\top w + b &\geq 1 - \xi_i \qquad \text{for} \quad y_i = 1, &(2.3.4)\\
x_i^\top w + b &\leq -1 + \xi_i \qquad \text{for} \quad y_i = -1 &(2.3.5)
\end{aligned}
$$

For the representation (2.3.2) – (2.3.5) when 1 appears on the right hand side the margin equals $2/\|w\|$. Here $\|w\|$ is the Euclidean norm or the length of vector w.

Only the observations lying on the margin boundaries or on the wrong side of the margin determine the SVM solution. These observations are marked with bold crosses and zeros. They are called support vectors, hence the name of the method. This contrasts to logit where all observations are used to derive the solution.

The primal minimisation problem to be solved is convex and has a unique solution:

$$
\min_w \frac{1}{2}\|w\| + \sum_{i=1}^{n} C_i \frac{\xi_i}{\|w\|} \tag{2.3.6}
$$

$$
\text{s.t.} \quad y_i(x_i^\top w + b) \geq 1 - \xi_i, \tag{2.3.7}
$$

$$
\xi_i \geq 0 \tag{2.3.8}
$$

Here (2.3.4) and (2.3.5) are rewritten as one constraint, where n is the number of companies. It is easier to see that the problem is convex if the optimised functional in (2.3.6) is rewritten as $\frac{1}{2}\|w\|^2 + \sum_{i=1}^{n} C_i\xi_i$. The first term is the inverse margin, which equals $2/\|w\|$. By minimising this term the margin is maximised. The second term is a sum of weighted errors that are measured as a distance to a misclassified observation i from the boundary of its class $\xi_i/\|w\|$. The parameters C_i's which are called capacity represent the penalty weights of in-sample false classifications for each company observation i. The SVM will give priority to the correct classification of the companies with higher C_i's. Capacity is related to the width of the margin zone. Smaller C_i's are associated with bigger margins. In our case C_i are set equal for the same class. In order to make SVMs comparable for a different number of observations and various ratios between solvent and insolvent companies C_i's are computed as $c/2n_+$ for insolvent and $c/2n_-$ for solvent companies. Here n_+, and n_- are the numbers of insolvent and solvent companies in the training set, c is the coefficient that is used to control the capacity of the SVM. In contrast to C_i it is invariant of the number of observations in the training data set and provides a convenient basis for comparing SVMs. This formulation implies that in a sample with mostly solvent companies, misclassifications of insolvent companies are given a higher weight. If the number of solvent and insolvent companies is the same, then $C_i = c/n$.

The primal problem (2.3.6) – (2.3.8) rewritten in a Lagrangian formulation is

$$\min_{w_k,b,\xi_i} \max_{\alpha_i,\mu_i} L_P = \frac{1}{2}\|w\|^2 + \sum_{i=1}^{n} C_i\,\xi_i - \sum_{i=1}^{n} \alpha_i\{y_i(x_i^\top w + b) - 1 + \xi_i\} - \sum_{i=1}^{n} \xi_i \mu_i \qquad (2.3.9)$$

The Karush-Kuhn-Tucker (KKT) Conditions or first order optimality conditions are:

$$
\begin{aligned}
\frac{\partial L_P}{\partial w_k} &= 0 \quad \Leftrightarrow \quad w_k = \sum_{i=1}^{n} \alpha_i y_i x_{ik}, \quad k = 1, ..., d && (2.3.10)\\
\frac{\partial L_P}{\partial b} &= 0 \quad \Leftrightarrow \quad \sum_{i=1}^{n} \alpha_i y_i = 0, && (2.3.11)\\
\frac{\partial L_P}{\partial \xi_i} &= 0 \quad \Leftrightarrow \quad C_i - \alpha_i - \mu_i = 0, && (2.3.12)\\
\alpha_i\{y_i(x_i^\top w + b) - 1 + \xi_i\} &= 0,\\
\mu_i \xi_i &= 0,\\
y_i(x_i^\top w + b) - 1 + \xi_i &\geq 0,\\
\alpha_i &\geq 0,\\
\mu_i &\geq 0,\\
\xi_i &\geq 0
\end{aligned}
$$

where x_{ik} is the k-th characteristic of company i and α_i are the Lagrange multipliers. The dual problem is equivalent to the primal one since the minimised function is convex (Gale et al. (1951)). By substituting equations (2.3.10) – (2.3.12) into the primal Lagrangian the dual problem is derived:

$$
\begin{aligned}
\max_{\alpha_i} \sum_{i=1}^{n} \alpha_i - \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^\top x_j, \qquad (2.3.13)\\
\text{s.t.} \quad 0 \leq \alpha_i \leq C_i,\\
\sum_{i=1}^{n} \alpha_i y_i = 0
\end{aligned}
$$

The n Lagrange multipliers α_i are the free parameters to be estimated. They represent the weights with which each observation influences the solution (see (2.3.16) and (2.3.21)). Those observations have higher weights which are harder to classify, i.e. which lie closer to the margin zone. On the contrary, the coefficients in the logistic regression are the weights assigned to each variable and can not be directly compared to Lagrange multipliers. Problem (2.3.13) can be equivalently expressed in a matrix notation:

$$\begin{aligned} &\max_{\alpha} \iota^\top \alpha - \alpha^\top H \alpha, \\ &\text{s.t.} \quad 0 \le \alpha \le C, \\ &\qquad\quad y^\top \alpha = 0. \end{aligned} \tag{2.3.14}$$

Here α is a vector of Lagrange multipliers, ι is a vector of 1's, y is a vector of company classes, $+1$ for solvent or -1 for insolvent ones and C here is a vector of the coefficients C_i; all vectors are of size $n \times 1$. The n components of the vector α are obtained as the solution of the constrained maximisation problem (2.3.14). The i, j'th element of the matrix H is

$$h_{ij} = y_i y_j x_i^\top x_j = y_i y_j \sum_{k=1}^{d} x_{ik} x_{jk} \tag{2.3.15}$$

The reader who desires to construct an SVM independently may find the problem formulation in the matrix notation (2.3.14) more convenient. The SVM problem is a classical quadratic optimisation problem (Fletcher (1987)) that can be solved with numerous software packages such as Matlab (routines *minq* or *minqdef*) or using algorithms specifically developed for the SVM such as the Sequential Minimal Optimisation (SMO) (Platt (1998)).

Equation (2.3.10) of the KKT optimality conditions determines the weights w_k, $k = 1, \ldots, d$ for the k-th characteristic of a company. By substituting (2.3.10) into (2.3.1) the classification rule is derived:

$$f(x) = x^\top w + b = x^\top \sum_{i=1}^{n} \alpha_i y_i x_i + b = \sum_{i=1}^{n} \alpha_i y_i x^\top x_i + b \tag{2.3.16}$$

$$\begin{cases} f(x) < 0 & \Rightarrow x \text{ is solvent,} \\ f(x) \geq 0 & \Rightarrow x \text{ is insolvent.} \end{cases}$$

To derive the coefficient b the fact that the separating hyperplane $f(x) = 0$ (see Figure 2.2) lies equidistant from the hyperplanes bounding the classes will be used:

$$\begin{aligned} x_+^\top w + b &= 1 \qquad \text{for} \quad y_+ = 1, & (2.3.17) \\ x_-^\top w + b &= -1 \qquad \text{for} \quad y_- = -1 & (2.3.18) \end{aligned}$$

where x_+ is any support vector that lies on or 'supports' the hyperplane for $y = 1$ and x_- is any support vector that lies on the hyperplane for $y = -1$. Both x_+ and x_- have dimensions $d \times 1$. By summing (2.3.17) and (2.3.18) we obtain the following equation:

$$b = -\frac{1}{2}\left(x_+^\top + x_-^\top\right) w = -\frac{1}{2} \sum_{i=1}^{n} \alpha_i y_i \left(x_+^\top + x_-^\top\right) x_i. \tag{2.3.19}$$

To reduce numerical errors when training the SVM it is desirable to use averages over all x_+ and x_- instead of two arbitrary chosen support vectors.

Note that the classification rule (2.3.16) depends only on the scalar product $x^\top x_i$, not on the original x and x_i. This makes possible a 'kernel trick', i.e. an implicit mapping of low dimensional data into a highly dimensional Hilbert feature space and performing a linear classification there, e.g. with an SVM. A kernel transformation corresponds to (i) performing a variable transformation and (ii) taking a scalar product of transformed variables.

In practice $x^\top x_i$ in the SVM formulation (2.3.13) is replaced with a kernel function $K(x, x_i)$ which represents a scalar product in a feature space (Weyl (1928)). Then the elements of the matrix H in (2.3.14) are $h_{ij} = y_i y_j K(x_i, x_j)$. A kernel function must satisfy the Mercer conditions (Mercer (1909)), i.e. be symmetric and semi-positive definite as a scalar product. It can map data into infinitely dimensional spaces as in the case with Gaussian kernels. The number of Lagrange multipliers α_i – parameters to be estimated – is n and can be large for large data sets. However, by selecting a small C_i's and, hence, a narrow interval $[0, C_i]$ in which α may vary overfitting and extremely high complexities of the SVM classifier can be avoided.

Figure 2.3 shows a simple mapping example. The quadratic kernel function

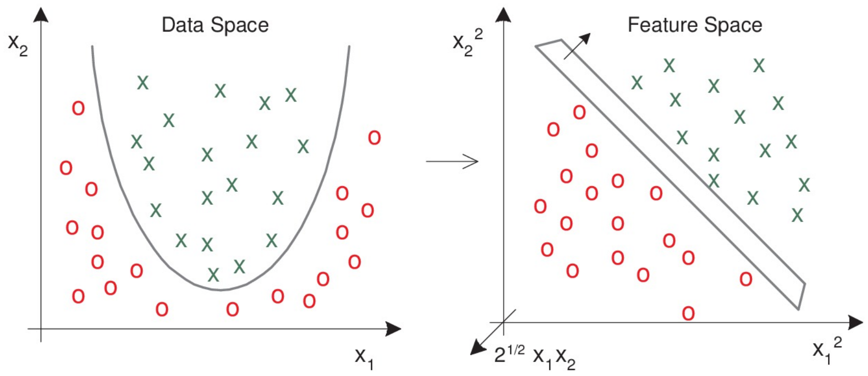
$$K(x, x_i) = (x^\top x_i)^2 \tag{2.3.20}$$

maps two dimensional data into a three-dimensional space of features. The three features correspond to the three components of a quadratic form in two dimensions: $\tilde{x_1} = x_1^2$, $\tilde{x_2} = \sqrt{2}x_1x_2$ and $\tilde{x_3} = x_2^2$. The transformation from a two dimensional data space into a three dimensional feature space is $\Psi(x_1, x_2) = (x_1^2, \sqrt{2}x_1x_2, x_2^2)^\top$. However, there is no need to know the transformation Ψ explicitly and the kernel $K(x_1, x_2) = \Psi(x_1, x_2)^\top \Psi(x_1, x_2)$ can equivalently be applied to represent quadratic dependencies between input variables. The data separable in the data space of x_1 and x_2 only with a quadratic function will be separable in the feature space of $\tilde{x_1}$, $\tilde{x_2}$ and $\tilde{x_3}$ with a linear function. Thus, a non-linear SVM in the data space is equivalent to a linear SVM in the feature space. The number of features is growing fast with the dimension of the data d and the degree of the polynomial kernel making a direct data transformation not feasible and the advantages of the data transformation via a kernel obvious.

By substituting the scalar product in (2.3.16) with a kernel function a non-linear score function f is derived:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b \tag{2.3.21}$$

Figure 2.3: Mapping from a two-dimensional data space into a three-dimensional space of features $\mathbb{R}^2 \mapsto \mathbb{R}^3$.



where, by analogy with (2.3.19):

$$b = -\frac{1}{2} \sum_{i=1}^{n} \alpha_i y_i \left\{ K(x_+, x_i) + K(x_-, x_i) \right\} \tag{2.3.22}$$

The non-parametric score function (2.3.21) does not have a compact closed form representation.

In this analysis an SVM with an anisotropic Gaussian or radial basis kernel is applied:

$$K(x, x_i) = \exp\left\{ -(x - x_i)^\top r^{-2} \Sigma^{-1} (x - x_i)/2 \right\} \tag{2.3.23}$$

where r is a coefficient and Σ is a scaling matrix, which in our case is a variance-covariance matrix of the training characteristics x. The k_1, k_2-th element of the matrix is:

$$\sigma_{k_1,k_2} = \frac{1}{n} \sum_{i=1}^{n} \left(x_{i,k_1} - \frac{1}{n} \sum_{j=1}^{n} x_{j,k_1} \right) \left(x_{i,k_2} - \frac{1}{n} \sum_{j=1}^{n} x_{j,k_2} \right) \tag{2.3.24}$$

Here σ_{k_1,k_2} is the covariance between two financial ratios x_{k_1} and x_{k_1}, e.g. a profitability and a leverage financial ratio. Σ is used to bring all variables to the same scale and exclude the excessive influence of the variables with high variance. The ability to use differently scaled data explains the term 'anisotropic' in the kernel name. Before computing Σ and training an SVM the outliers should be processed, e.g. capped. The coefficient r is related to the complexity of classifying functions: the higher the r is, the lower is the complexity. If kernel functions allow for sufficiently rich feature spaces, the performance of SVMs with different kernels is comparable in terms of out-of-sample forecasting accuracy (Vapnik (1995)). Note that only the capacity C_i and the complexity coefficient r are to be set a priori. The Lagrange multiplies are the free parameters that are computed when training the SVM.

The SVM has a substantial advantage in comparison to the logistic regression with transformed variables, namely, it does not require to specify the transformation but estimates it from a broad range of possible ones defined implicitly by the kernel function type and the SVM capacity coefficient. This advantage of the SVM is fully revealed when data are new or the relevance of well known transformations must be tested.

2.4 Empirical Results

In this section, first, the univariate analysis of each financial ratio in relation with probability of default (PD) is presented. Second, the variable selection procedure for SVM and logit and the results are discussed. Also, a comparison between the prediction performance of each method is provided by analysing the out of sample accuracy ratio of each model.

2.4.1 Univariate Analysis of the Predictors of Default

The analysis of financial ratios and their individual discriminating power as predictors of default can be concisely done by estimating univariate dependence of PD from each variable. Since the range of each ratio can change significantly, all predictors are represented with their percentiles. Univariately estimated PDs are presented in Figures 2.4 – 2.10. They were obtained as k nearest neighbor estimates (k-NN) with Gaussian weights:

$$PD(q) = \frac{\sum_{i=1}^{n} \mathcal{I}(y_i = 1) e^{-\frac{(q-q_i)^2}{2\sigma^2}}}{\sum_{i=1}^{n} e^{-\frac{(q-q_i)^2}{2\sigma^2}}} \tag{2.4.1}$$

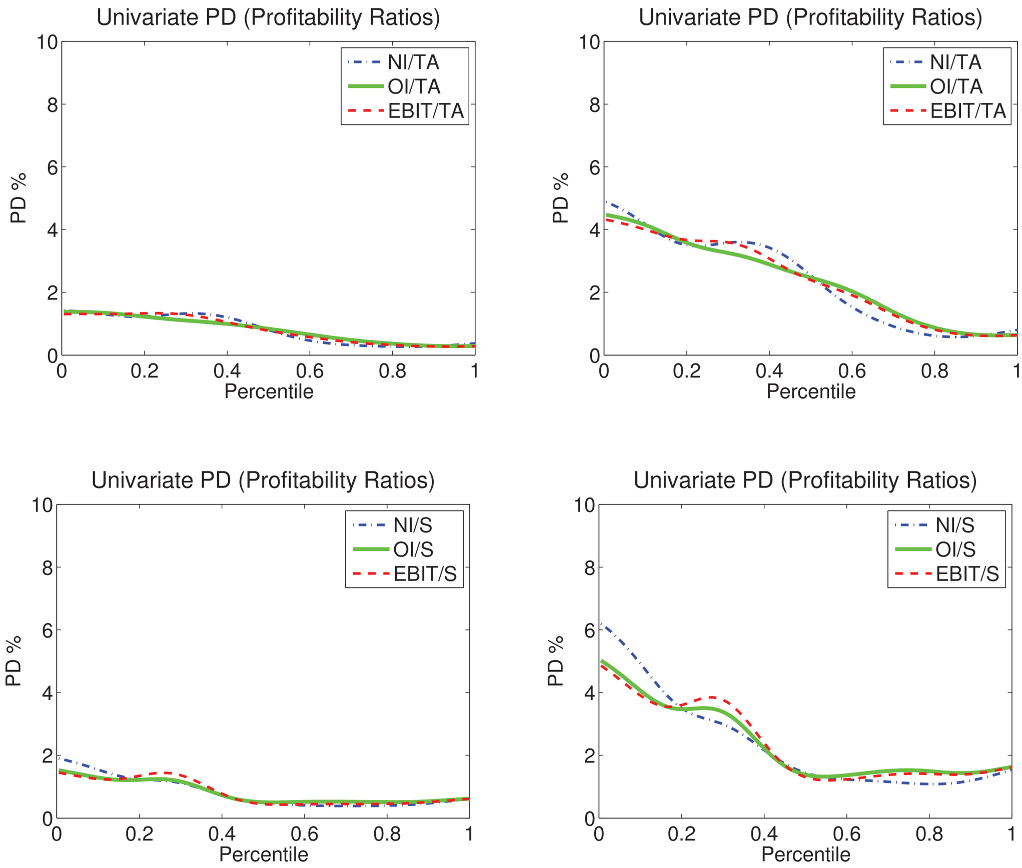
where $0 \leq q \leq 1$ is a percentile of a company for which PD is estimated, q_i is the percentile of company i of the data set and the smoothing parameter σ is set to 0.08. $\mathcal{I}(y_i = 1)$ is the distress indicator which equals 1 if $y_i = 1$ when company i is defined as distressed and 0 otherwise.

The variables differ substantially in their predictive power. For instance, variables EBIT/TA, CL/TA and log(S) indicate strong predictive power and also traditionally appear in the literature as strong indicators. In contrast some variables such as STD/D, AR/S and Sales-Growth show less discriminating power.

Another important observation from the plots is that some predictors, many of which with high discriminating power, such as OK/TA, CL/TA, CA/CL, CL/TL, INT/D, EBIT/INT paid and log(TA) have a non-monotonic dependence with PD.

The relationship between each predictor of default with PD and their predic-

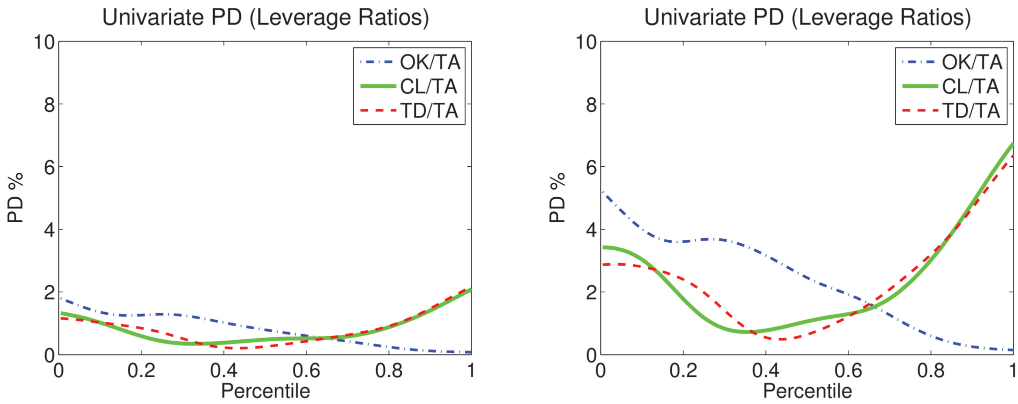
Figure 2.4: Univariate probabilities of default for *Profitability Ratios* pooled over countries and years.



Note: Horizon: *Design 1* (left panel), Horizon: *Design 2* (right panel).

tive power is analysed on data pooled over countries and years. The results are presented for the two horizon designs, *Design 1* and *Design 2*.

Figure 2.5: Univariate probabilities of default for *Leverage Ratios* pooled over countries and years.



Note: Horizon: *Design 1* (left panel), Horizon: *Design 2* (right panel).

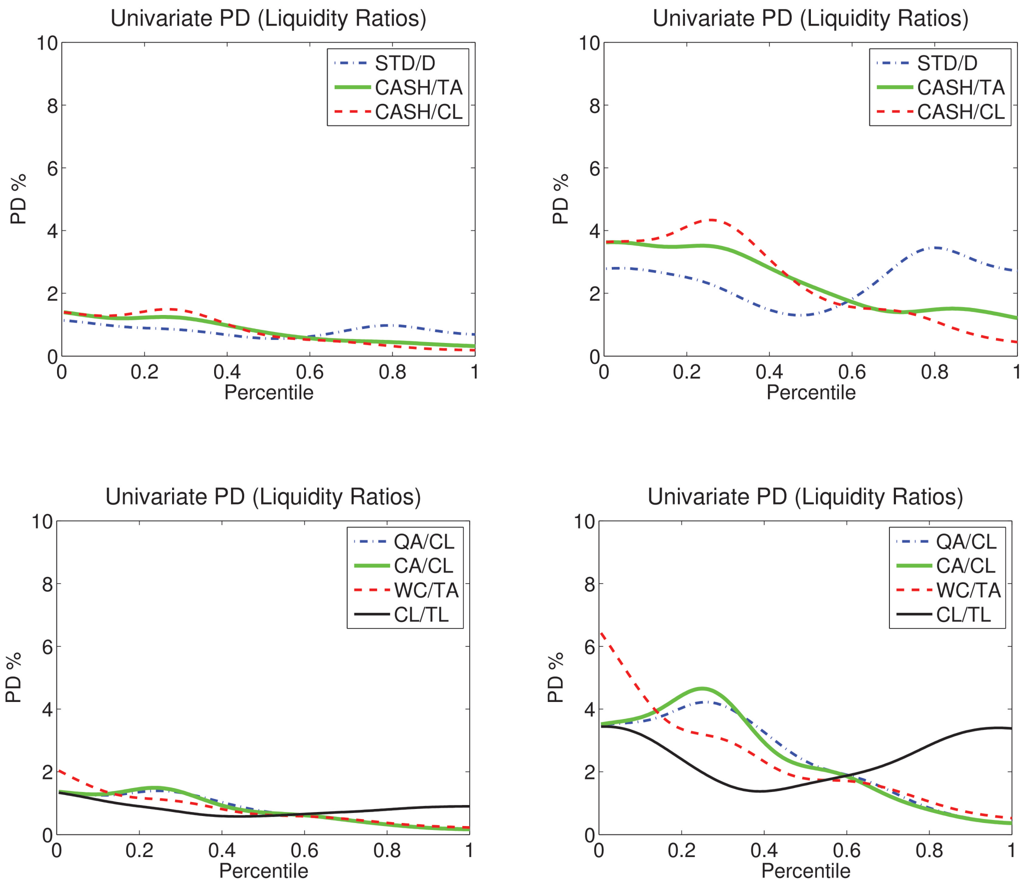
2.4.2 Variable Selection and Rating Model Comparison

The criterion for comparing different models is a robust accuracy measure, the median Accuracy Ratio (AR) estimated on bootstrapped subsamples. AR is the ratio of two areas (i) between the cumulative default curves for the model being evaluated and the model with the zero predictive power and (ii) between the cumulative default curves for the ideal model and the model with the zero predictive power (Figure 2.11). AR is used since it is not sensitive to a monotonic transformation of a score in contrast to other accuracy measures such as hit rate or α and β errors.

The bootstrap procedure (Efron and Tibshirani, 1993) for model comparison starts with the selection of two non-overlapping random subsamples of 1000 observations (500 non-defaulting and 500 defaulting firms) from the original data set. One of those subsamples is used as a training set and the other one as a testing set. A classification model (SVM or logit) is trained on the former and its AR is estimated on the latter. The procedure is repeated 100 times creating a set of 100 estimates of AR from which the median is computed and used for the comparison of models. The model with the highest median AR is preferred.

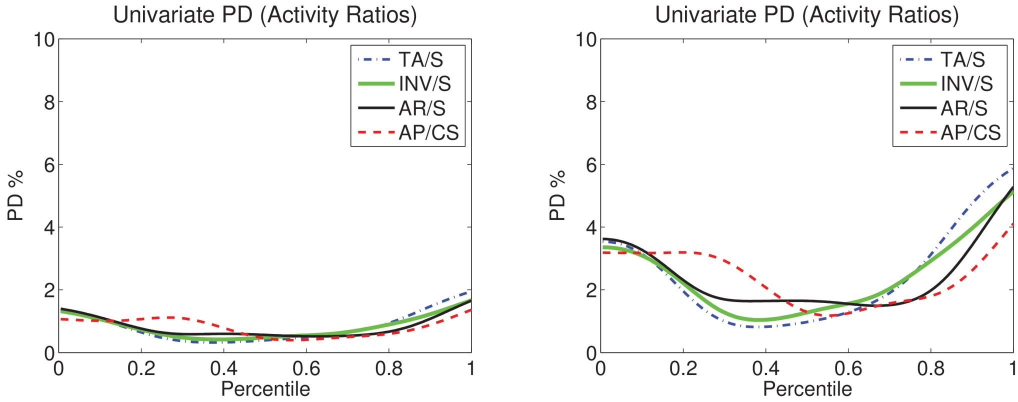
All data were first cleaned from outliers by capping them: if $x < q_{inf}(x)$ then

Figure 2.6: Univariate probabilities of default for *Liquidity Ratios* pooled over countries and years.



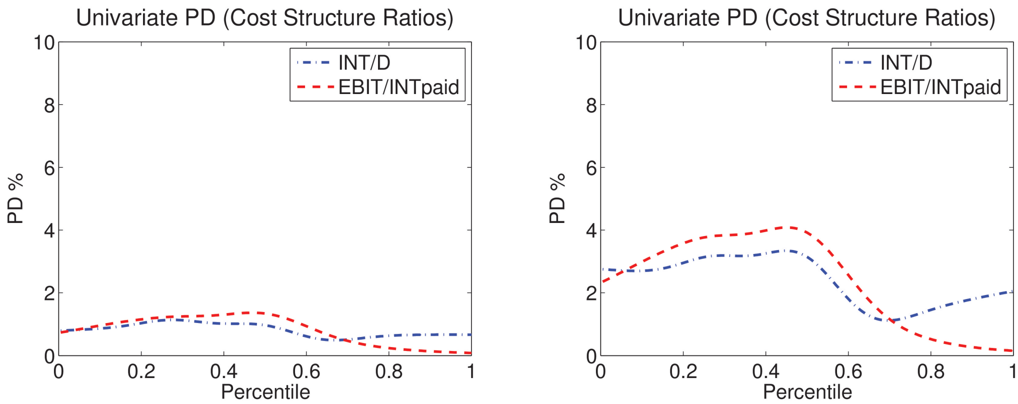
Note: Horizon: *Design 1* (left panel), Horizon: *Design 2* (right panel).

Figure 2.7: Univariate probabilities of default for *Activity Ratios* pooled over countries and years.



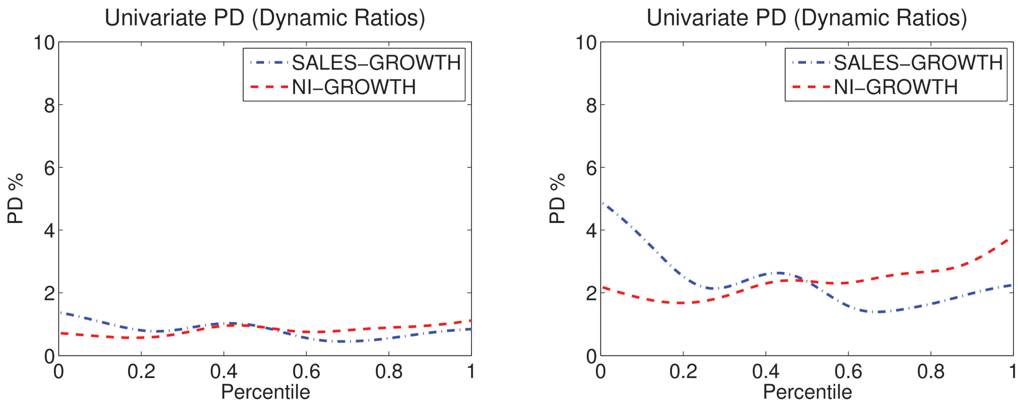
Note: Horizon: *Design 1* (left panel), Horizon: *Design 2* (right panel).

Figure 2.8: Univariate probabilities of default for *Cost Structure Ratios* pooled over countries and years.



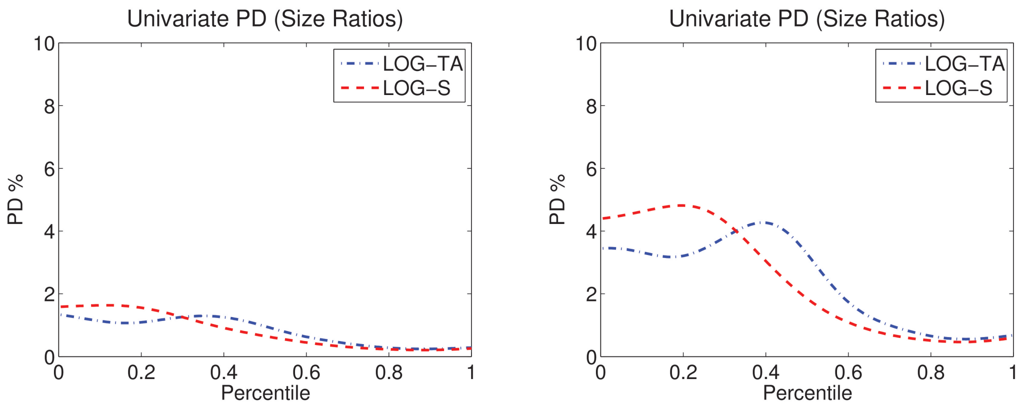
Note: Horizon: *Design 1* (left panel), Horizon: *Design 2* (right panel).

Figure 2.9: Univariate probabilities of default for *Dynamic Ratios* pooled over countries and years.



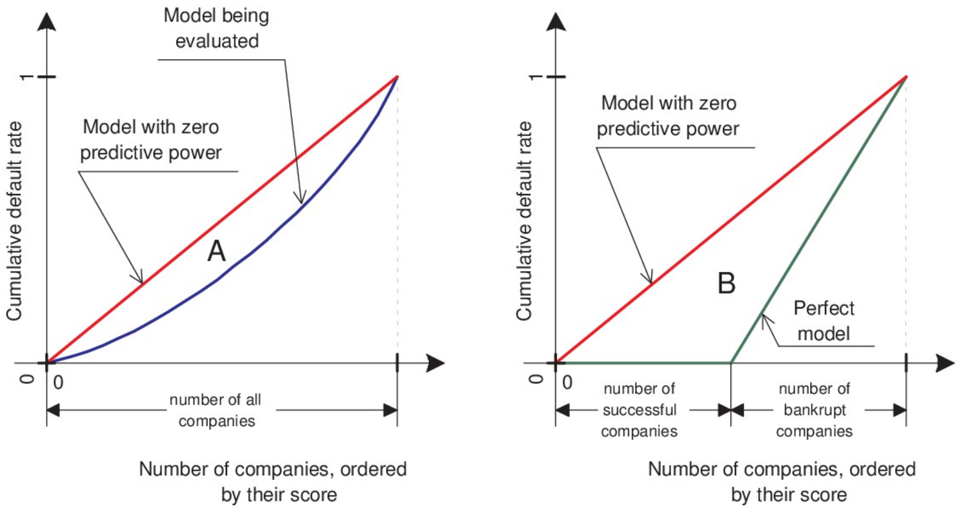
Note: Horizon: *Design 1* (left panel), Horizon: *Design 2* (right panel).

Figure 2.10: Univariate probabilities of default for *Company Size* pooled over countries and years.



Note: Horizon: *Design 1* (left panel), Horizon: *Design 2* (right panel).

Figure 2.11: Accuracy Ratio (AR) is the ratio of two areas A and B.



$x = q_{inf}(x)$ and if $x > q_{sup}(x)$ then $x = q_{sup}(x)$. Here $q_{inf}(x) = Median(x) - 1.5IQR(x)$ and $q_{sup}(x) = Median(x) + 1.5IQR(x)$. Secondly, all data were standardised as $x_{new} = (x - median(x))/\sigma(x)$. This was done to avoid an excessive influence of the variables with a higher dispersion. These transformations are routinely applied to the data prior to analysis.

Variable selection was performed using the forward selection procedure which starts with univariate models. At step one the first variable is selected that produces the most accurate univariate model as judged by its median AR which is estimated by bootstrapping. At step two, in addition to this variable, the second variable from the remaining is chosen which has the highest median AR among all alternatives. At step three a trivariate model is selected, etc. The variables selected by logit and SVM for pooled data are presented in Table 2.6. After step four the accuracy of both the logit and SVM models does not experience any significant improvements, which is evident from very high p-values.

The SVM was always applied with $R = r\sqrt{d/2}$ and $C = (c/n)(2/d)$, where r and c were chosen based on the values reported as performing well for company rating (Lacerda and Moro, 2008; Chen et al., 2011). These two parameters of the SVM used in our study were $r = 2.5$ and $c = 1$ for a low complexity SVM with

Table 2.6: Variables selection results at each step by the forward selection procedure for logit and SVM for the pooled data.

	logit				SVM ($R = 2.5, C = 1$)			
Step	Variable	Med. AR	p_{max}	p	Variable	Med. AR	p_{max}	p
1	TD/TA	57.5	0	–	TD/TA	57.5	0	–
2	log(S)	69.0	0	0	log(S)	69.7	0	0
3	CL/TA	71.1	0	0	CL/TA	71.7	3	5
4	log(TA)	**73.2**	–	**0**	TA/S	**73.5**	–	**3**
5	WC/TA	73.3	–	19	RV	73.4	–	75

For computing the median AR for each combination of variables and the distributions of AR required for the tests, 100 bootstrapped subsamples were used. The confidence level p_{max} is reported for the test with H_0: the model is not significantly different from the four-variable model which was selected; p corresponds to the H_0: a model is not significantly different compared to a previous reduced model which has one variable less. Median AR, p_{max} and p are reported in percentage points.

high generalisation ability, which is expected to perform well on a broad range of data sets. The performance of the SVM can be potentially further increased by optimising r and c for the studied data. The transformations for computing R and C figuring in the SVM formulation (see Appendix B) were applied to keep the SVM invariant of the data dimension d and the number of observations in the training set n.

As the Table 2.6 indicates both models considered – logit and SVM – have selected the first three variables identically: TD/TA, log(S), CL/TA. The fourth variable selected by the SVM is TA/S, while log(TA) was selected by logit. These variables form the basis for our model comparison.

2.4.3 Forecasting Accuracy

Figure 2.12 represents the time series of Accuracy Ratios (AR) for pooled data and a separate country with the highest number of distressed observations, China. The training dataset are collected from the year indicated in the plots along the horizontal axis. The testing set data are collected for the year $T + 2$, where T is the training set year. The used default horizon specification is *Design 2*. This arrangement guarantees that there are no overlapping observations in the data sets and forecasting is made out-of-sample. The parameters of the SVM are $r = 2.5$ and $c = 1$. The variables are the same ones selected by variable selection procedure. For SVM these variables are: TD/TA, log(S), CL/TA and TA/S and for logit: TD/TA, log(S), CL/TA and log(TA).

As it is evident from Figure 2.12, SVM usually outperforms logit in forecasting corporate distress. The difference in AR can be as high as 7.5%, as it is the case for China in 2005. On the other hand there are much fewer years when the SVM underperformed compared to the logit. The maximum difference in this case is only 2.4% in 2003. For the pooled data in seven years out of eight the SVM has a higher performance than the logit, although the differences in this case are more moderate than for China.

A similar conclusion about a higher predictive power of the SVM can be reached from analysing Figure 2.13. It reports the distribution of the differences in AR between the SVM and logit estimated on 100 bootstrapped subsamples of the data pooled across countries and years. Although the average improvement is moderate, around 0.5%, the SVM can achieve a much higher relative improvement for extreme scenarios. This is evident from a longer right tail of the probability density function. In other words, the SVM has a lower model misspecification risk compared with logit, both on average and in the extreme cases.

Figure 2.12: AR of 2 year probabilities of default estimated with SVM and logit for pooled data and China. Horizon: *Design 2*.

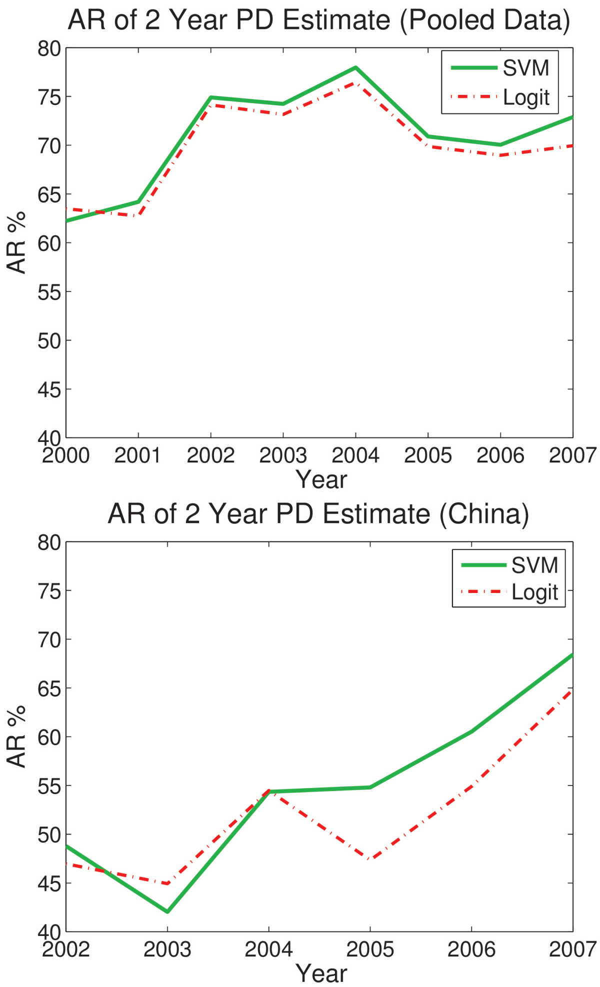
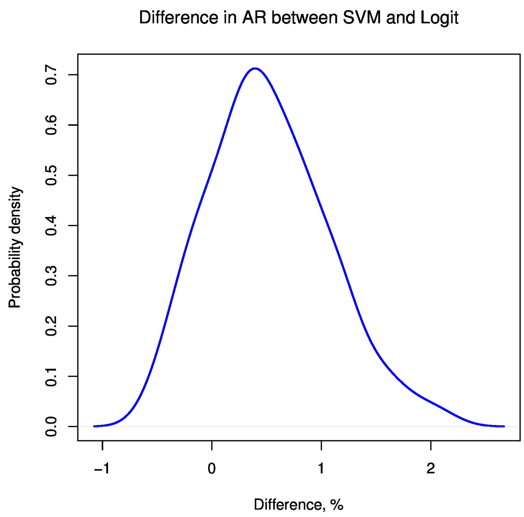


Figure 2.13: The distribution of differences in AR for the SVM vs. logit estimated on 100 bootstrapped subsamples for a four-variable model on pooled data.



Note: Horizon: *Design 2*. A Gaussian kernel estimator was used with the bandwidth 0.191.

2.5 Conclusion

The focus of our study is the analysis of the ability of two models, SVM and logit, to predict distress in the Asian and Pacific region in various settings.

Both models selected only four financial ratios as predictors of default, whereas three financial ratios are the same: TD/TA, log(S) and CL/TA. They are leverage ratios and a company size. Surprisingly, no profitability ratios were selected.

A strong U-shaped dependence of PD from the leverage and activity ratios implies the existence of the optimal capital structure (TD/TA=15%, the figure being in accordance with the existing literature) and inventory stock (Inv/S=38%).

Comparison of forecasting accuracy reveals that the SVM has a lower model risk than the logit. Firstly, on average SVM is more accurate than logit. Secondly, in the extreme cases when discrepancies between the two models are the largest, the predictive power of the logit can fall significantly below the SVM, while the probability that the SVM will significantly underperform relative to the logit is much smaller.

Overall, an SVM with a high generalisation ability appears to be a promising method for distress forecasting in the Asian and Pacific region providing a reduction of model risk and a more robust performance compared to the logit. This finding has also been confirmed in studies by Lacerda and Moro (2008) and Dellepiane et al. (2015).

Chapter 3

Corporate Distress and Innovation in the US

3.1 Introduction

The measures employed to analyse bankruptcy risk are mostly based on a set of accounting information represented as financial ratios which indicate current financial position and operating performance of the firms. These financial ratios include profitability ratios such as return on assets and profit margin, liquidity ratios such as current ratio, efficiency ratios such as asset turnover, growth prospects information such as market-to-book ratio, leverage ratios such as debt to total assets and other groups of ratios indicating structure and size of the business such as total assets. Among all introduced group of financial ratios, profitability, leverage and size have been found most important in many studies (see for instance Altman, 1968; Ohlson, 1980; Carey and Hrycay, 2001; Becchetti and Sierra, 2003; Bonfim, 2009; Duan et al., 2012). This information, however, does not reflect the capability of the firm in the technology competition and its technology competency among its peers. This can be a more important element in the survival of a firm, especially for those operating in technology intensive industries. In addition, use of income statement and balance sheet in accounting based models makes them sensitive to accounting standards.

Prior studies which focus on ranking firms based on distress risk by measuring probability of default (PD) fail to provide evidence on firms classified as distressed with higher risk that benefit from higher returns. Several studies such as Dichev (1998) find that the return of distressed firms are lower than average returns and Griffin and Lemmon (2002) indicate that the low returns of distressed firms are related specifically to highly distressed firms with low book to market ratio. Although these high risk firms have low current returns, they present high sales growth and R&D expenses. In the absence of a less conservative accounting policy allowing capitalisation and amortization of R&D expenditures, these firms have to fully expense the R&D spending which results in lower net income. In fact, increasing R&D expenditures over time considerably affects the accounting based measures of firm performance. This is the reason for increasing the number of solvent R&D intensive firms in distress classification. Therefore, accounting based models in distress forecasting have become less effective due to the upward trends seen in research and development activities and increase the likelihood of distress misclassification (Franzen et al., 2007).

In other words, while the link between tangible assets and firm financial performance is rather intuitive and well investigated in the literature, firms, especially the technology-driven ones with few tangible assets and higher R&D expenditures, are potentially exposed to a deceptive credit assessment. Essentially, this means that new measurement and information about level of technological knowledge is needed for a more efficient assessment of firms' future financial performance especially for technology intensive firms. Venues to bridge such informational deficit in credit rating assessment have been suggested in the literature (Neuhäusler et al., 2011). Ernst (2003) states that a large amount of technological knowledge is disclosed in patent databases.

Patents as a measure of R&D activities are examined and granted by the patent office and are also classified according to standardized schemes which facilitates detailed analysis of specific technological aspects. Compared to other sources of information for timely recognition of technological activities, patents are often considered as the best source (Ernst, 2003). Moreover, patent application processing usually takes up to three years before they are granted, technology is commercialized and income is generated. However, the information about patent application is disclosed to the public after 18 months of the priority date of the application. This indicates that patent data is not only relevant for firms' financial assessment but also it is useful for forward looking analysis (Ernst, 2001).

The relevance of patent information in the context of credit rating has been confirmed also empirically. Pederzoli et al. (2013) show that the value of a firm's patent portfolio always reduces the PD. In an analysis by Wilbon (2002), firms with stronger intellectual property right portfolio securing their products are more likely to survive in the first five years after initial public offering (IPO). Helmers and Rogers (2010) also find a positive relationship between both trademarks and patents and firm survival rates.

The most common corporate credit rating model applied by academics and practitioners is logistic regression (LR). With a specified time period, e.g. two years, an LR model is fit to historical data for predicting the probability that a firm will go bankrupt within the specified time period, as a function of the firm's performance variables, also called predictors. In this set up a lower PD means better creditworthiness, therefore a cut-off point is set to distinguish the risky firms from the healthy ones.

Many other statistical methods for credit rating have also been introduced which aim to fit more complicated models with higher degree of nonlinearity between PD and predictors such as neural networks (Lee et al., 1996), Bayesian network (see e.g. Sarkar and Sriram, 2001) and support vector machines classifiers (e.g. Chen et al., 2011). However, Hand (2006) argued that the potential improvements in the performance of more complex models are often compromised by other uncertainties that arise by the added complexity. Moreover, in a study by Baesens et al. (2003), it is concluded that many such complex models generally have similar performance to LR in terms of predicting probability of default.

Survival analysis is an alternative to LR in credit risk analysis. Survival analysis models the distribution of the time T to default as opposed to LR which estimates probability of default within one specified period of time. The distribution of time T in survival analysis is allowed to be a function of a firm's performance indicators via a proportional hazard (PH) survival model. Im et al. (2012) state several advantages of PH survival analysis over LR in terms of predicting default probability within a single period of time. First, survival analysis conducts a mechanism that takes into consideration the most recent information. Second, it provides more information on the predicted behavior of time to default T via the predicted distribution. This information includes for example mean of the predicted distribution for each firm as well as a quantitative understanding of uncertainty expected in T via upper and lower quantiles of the predicted distribution. Third, survival analysis can be modified to incorporate dynamic macroeconomic variables which are input as time series data into the model, (see for example Shumway, 2001; Bellotti and Crook, 2009; Im et al., 2012) that have applied PH survival models for credit rating.

The aim of this research is to extend on previous literature on the influence of innovation activities and more specifically patenting on corporate bankruptcy. To do so, a panel data set of 10,646 US listed firms is used which contains accounting information and also a patent indicator distinguishing patenting firms from non-patenting firms. We replicate the PH survival analysis (Cox, 1972; Im et al., 2012) and extend the main accounting and market based predictors widely used in the previous studies (such as Ohlson, 1980; Campbell et al., 2008; Chava and Jarrow, 2008; Löffler and Maurer, 2011) by a patent application indicator.

3.2 Motivation and Literature Review

The accuracy of credit ratings depends not only on qualitative but also quantitative factors. However, while the ability of accounting indicators as inputs for credit ratings is largely acknowledged, the role of non-accounting indicators remains ambiguous. One of the most important indicators reflecting a firm's status is its innovative activities. This results from the fact that intangible assets are a fundamental determinant of corporate's financial status and its competitive advantage and, hence, investors view inventive activity of a firm as an asset rather than as an expense (Hall et al., 2007).

Our motivation to investigate the relationship between innovation activities and bankruptcy is driven by the fact that while many bankruptcy studies consider a wide set of accounting data, there have not been many studies looking at the effect of technology competition and innovation activities on bankruptcy. Poor technological competitiveness might not be reflected in its accounting ratios, but it could have an enormous effect on its financial performance in the future, which could result in bankruptcy. In other words, usually none of the traditional indicators used in bankruptcy analysis would directly incorporate the ongoing technology developments of a firm, and particularly the level of its competence. This is much more important for firms which operate in technological intensive industries. Greenwood and Jovanovic (1999) and Hobijin and Jovanovic (2001) demonstrate that new technologies are distressing for firms unable to demonstrate technological competence in the long run.

3.2.1 Bankruptcy and Innovation

Innovative firms operating in high technology industries are very likely enhance their market share if they are able to develop and adopt the most recent updated technologies; however they are also exposed to high operational risk. Similarly, firms in technology driven competitive industries which are incapable to develop and adopt new technologies, can easily lose their market power and suffer low profitability and declining sales prospects, which result in financial distress and eventually bankruptcy.

The absence of technology development indicators in bankruptcy analysis, has been raised in several studies. For instance Franzen et al. (2007) discuss the poorer performance and accuracy of traditional indicators of financial distress in recent years and suggest modifications such as incorporating information about level of technological activities. Also, Franzen et al. (2007) aim to demonstrate the misrepresentation in accounting based indicators for bankruptcy prediction due to expensing of R&D investments. In return, they propose an adjustment to Ohlson (1980) bankruptcy prediction approach by capitalizing R&D investments. In fact, a firm's financial position and the likelihood of survival in the long term is affected by its technological capability. Thus, firms with very limited or no technological capabilities are expected be more financially constrained, especially in technology intensive industries.

The relationship between technology competition and bankruptcy has become more important as technological capability exerts a stronger effect of the patent system on the survival of a company (Eisdorfer and Hsu, 2011). The current patent system could be seen as a major battlefield for corporates (Eisdorfer and Hsu, 2011). Hall (2005) states that since the establishment of a patent specialised court (the Court of Appeals for the Federal Circuit, CAFC in the US) in 1982 and a few patent infringement cases publicised in the 1980s, patent competition has become fiercer. Intensive patent competition and doubled number of patent lawsuits between years 1984 and 1999 (Bessen and Meurer, 2005) is not surprising since there is a direct relationship between more patent filings and higher number of patent litigations. Obviously technology advances escalates patent competition, leading to stronger patent regulation.

Therefore, technological developments can be highly costly and distressing for firms through patent competition and patent system. A patent applicant firm can appeal for a preliminary order to prevent unauthorized imitation of the innovation that could impose high legal expenditures on its competitors (Lanjouw and Lerner, 2001). Also, when a patent holding firm sue another firm for unauthorized imitation of its patents, the litigation may postpone the defendant firm from operating in connection to that infringement. Such enforcement can lead the defendant firm into a severely constraint financial situation, if it's granted a request of injunction by court (Lanjouw and Lerner, 2001). Additionally, a publicising a patent litigation dampers the defendant's share price and reputation (Bhagat et al., 1994; Lerner, 1995), which imposes more difficulties on the defendant firm to survive the court order. Therefore, all explicit and implicit costs associated to a patent litigation can seriously distress the financial situation of the firm that loses the case (Lerner, 1995; Hall, 2005). This indicates that bankruptcies are expected to be more costly for such firms with less technological competition power which most likely are exposed to imitating their competitor's patent. Such imitating behavior is especially more risky in industries which are more sensitive to technological activities and competition.

3.2.2 Patents, Technological Competence and financial Performance

Considering the confirmed relationship between patent and financial condition of firms, information on companies' patent portfolios as an indicator of level of technological competition and innovation activities of firms can be used as an input for bankruptcy analysis. However, measuring inventive activity through patent data is far from a straightforward task. Complexity of the patent information is firstly related to high uncertainty and also highly skewed returns of R&D investments (Carpenter and Petersen, 2002). Secondly, it is related to increase in strategic patenting which is problematic for the use of patent data for valuation purposes. Firms which are strategic patenting oriented have quite few valuable patents because they do not patent to protect products against imitation, but rather to offset competitive powers. Consequently, with the trend in strategic patenting, there is an increasing number of low value patents. Hence, it has become complicated for outsiders to evaluate and differentiate valuable patents from the low value ones (Blind et al., 2006). Thirdly, noise in the patent data requires specific knowledge about patent systems to make the best use of the information.

In addition, the use of patent data as a proxy of inventive output has several shortcomings (Griliches, 1990; Smith, 2005). Firstly, not all inventions are patented, and also not all patented inventions turn into innovations. It must be considered that in some cases patent applications cannot account for innovations when these, for example, occur in the production processes. Moreover, there are other ways to protect inventions different from patenting that can be preferred by firms. For example, firms can opt for the protection offered by secrecy instead of exploiting their competitive advantage under the coverage of a patent right. Differences in patenting fees and rules also affect the propensity to patent innovations in different countries. The same point can be made with respect to some technologies and differences in patenting policies among countries. For instance, software patenting is possible in the US, whereas it is limited in Europe. This weakens the usefulness of patent data in a cross-industry comparison.

Another major problem of using the information related to patent is represented by the lack of economic value of patents (Arora et al., 2004; Lichtenthaler, 2009). This is related to the deflation of patent value that is driven by the increasingly large number of patent applications that are being filed around the world. This problem is amplified as strategic or defensive patenting is widely applied by companies to slow down competition in a specific market or to accumulate a patent portfolio to use as bargaining power. For example, for each meaningful patented innovation, there might be a number of satellite patents extending the scope of protection. With respect to a firm strategic behavior, patents are often used by companies for other purposes such as to disclose information about innovations which might have been otherwise kept secret and to signal the availability of important technology available to a firm; or to prevent others from acquiring rights to a certain technology (Guellec and de la Potterie, 2001). This kind of behavior resulted in “patent inflation” or “global patent warming”. Consequently, the distribution of patent value is skewed to the left or, in other words, only a small number of patents determine the value of patent portfolios (Gambardella et al., 2008).

Despite the above mentioned drawbacks, Eisdorfer and Hsu (2011) outline four advantages for applying patent information. First, unlike R&D expenditures that involve uncertainty, patents are indication of realized technologies influencing future operating performance. Second, patents are a measure of competition because they are exclusive to the business. Third, the necessity of defensive patent filings has been realized by many firms due to the surge of patent competition and litigation in many industries. Fourth, patents are a powerful tool in protecting higher income for the patenting firms than the income of non-patenting firms.

Furthermore, other implicit benefits of patents are outlined in literature. The first benefit is that patents can protect the firms technological space to be reduced by patents of the competitors. Second, patents can generate licensing income or they can be traded with other firms through cross-licensing. Third, patents can be used as bargaining power to negotiate with other firms to get access to new technologies. Fourth, patents can be used to expand market power internationally and enhance the firm’s reputation (Neuhäusler, 2012). Therefore, according to literature, patenting inventions arising from R&D activities are most likely to be protected from the possibility of exploitation by third parties and this makes patents a robust measure of the output of inventive processes. This justifies our proposition to use patent information in this research to assess the impact of patent applications on firms’ financial stability.

In a study by Eisdorfer and Hsu (2011) a new bankruptcy prediction model with a patent-based factor is presented which suggests causality between technology competition and bankruptcy. They also indicate a strong relationship between the information on the level of technological competitiveness of firms and the risk, costs and pattern of bankruptcy in technology driven industries. In this study a data set of patent applications and issues at firm-level is used and three findings are presented. First, the competitiveness in technology intensive industries is a better indicator for bankruptcies in short run than the typical accounting information applied for example in Z-score approach. Second, bankruptcies driven in intensive technology industries are less related to industry success and the business cycle. Economic intuition and the empirical evidence suggest that there are less bankruptcies in successful industries and when the economy is running productively. However, there is argument that this relationship is weaker for technology driven bankruptcies. The argument comes from the fact that technological innovations and patent activities typically improve the economy as a whole specifically in the technology driven industries (Hsu, 2009). However, at the same time, these innovations cause serious disadvantage for the firms that lose in the innovation competition, which could drive them to bankruptcy (Garleanu et al., 2009). The third finding is that, bankruptcies which are driven by patent competition are significantly more costly. This is the result of lower demand for products of the old technologies, quicker depreciation for inventories and equipment used for the old technologies, the declining reputation of firms that are capable enough to compete with the new and updated technologies and finally potential costs associated to patent litigation(Eisdorfer and Hsu, 2011). This means, while bankrupt firms typically face a steady decline in financial performance, a firm that is weak in the technological competition and has no competitive power could quickly reach a distressed position.

The importance of patent information for corporate bankruptcy analysis in the literature is also shown in a study by Neuhäusler et al. (2011). This study provides evidence of incorporation of patent information by Credit Rating Agencies (CRA) in their rating assessments. CRA as information intermediaries contribute to market efficiency by gathering data from different sources and giving opinion on creditworthiness of debt issuers. However, the question is whether CRA use patent data in their credit assessment and so help technology driven firms by providing clear credit assessment, including their intangible information and distinguishing between valuable and low value patent portfolios. This question is addressed by Neuhäusler et al. (2011) and their findings indicate that corporate credit ratings, similar to stock market valuations, reflect the future economic benefits associated to patents with strong impact of patent flows improving rating, indicating that companies which file a high number of patent applications per year receive a higher credit rating. The reason for the importance attached to patent flows is that CRA perceive patents as an innovative output associated with higher probability of future returns and also as a competitive weapon to protect the higher return.

As already observed, an increasing number of companies treat intellectual property (IP), in general and patents, in particular, as a central business asset (WIPO, 2011a). This asset is managed with a view to generating returns through, for example, licensing (Arora et al., 2004; Gambardellaa et al., 2007; Lichtenthaler, 2009). Moreover, patents are used as collateral for bank loans by patent holders, and as investment assets by financial institutions (Kamiyama et al., 2006). Research-oriented small enterprises and start-ups depend on IP to generate income and use IP to obtain external financing, including venture capital investments (WIPO, 2011b). This increasing trend brings more attention to the role of patenting on firms performance in general and financial distress analysis in particular which has been poorly identified in corporate bankruptcy literature.

In examining the link between patent information and bankruptcy analysis, the present study extends on the past research in several ways. First, it investigates the significance of patent applications on corporate credit default, whereas most of the previous studies have analysed the impact of other innovation factors, such as patent flow and patent citations (Neuhäusler et al., 2011) or the number of patent applications and patent issues in a year (Hsu, 2009). Second, it applies a hazard model which is expected to analyse bankruptcy more accurately compared to other bankruptcy models. Third, it investigates the impact of market based variables in combination with accounting variables in the context of credit rating. This motivation is driven by two previous studies: Shumway (2001) that argues about half of the accounting indicators that have been previously used to model bankruptcy are not statistically significant as bankruptcy predictors; Franzen et al. (2007) which objects effectiveness of the accounting based models in bankruptcy analysis due to the upward trends seen in research and development activities.

3.3 Data Description, Data Matching

3.3.1 Accounting Data

Data used in this study are collected from two databases. The first database which is provided by the Risk Management Institute (RMI) of the National University of Singapore (NUS) contains quarterly and annual financial reports, sector and industry information, default events data and stock prices for 15,789 listed US firms. The RMI database contains default information for 1,774 firms liquidating under Chapter 7 or seeking protection under Chapter 11 of the US bankruptcy code. This means 10.4% of the firms fall in one of these categories at least once in the time span from 1980 to 2010. The wide coverage of the default data along with the availability of patent information for US firms, obtained from other sources, facilitates the further research on the relationship between patenting and bankruptcy prediction.

The scope of this research covers non-governmental manufacturing firms and service providers. Therefore, companies operating in the financial sector, asset backed securities, funds and government owned enterprises are excluded.

To process the data in the form required for bankruptcy analysis, financial ratios are constructed using the accounting data. These ratios reflect company performance from four different perspectives: profitability, leverage, liquidity and size. In addition, a set of dummy variables are considered for sectors to distinguish the sectors in which the firm operates. Then, the accounts with missing positions are removed and the 5% and 95% percentiles are used as threshold to recap the remaining lower and upper outliers for every financial ratio.

Financial reports in the database are released quarterly, semi-annually and annually and reporting dates for companies are different and spread throughout the year. In this study we use quarterly reports. We index each quarterly financial report by a unique time stamp according to the year and month of the report in order to arrange the financial information on a regular monthly basis for all firms. Therefore, each quarterly report receives a time stamps unique to the month and year of the report. The resulting monthly indexing of accounting data enables

Table 3.1: The term structure of default.

Default Horizon	Chapter 7	Chapter 11	Total
5 year	1,166 (0.40%)	11,873 (4.10%)	13,039 (4.50%)
4 year	969 (0.30%)	9,777 (3.40%)	10,746 (3.70%)
3 year	743 (0.26%)	7,458 (2.59%)	8,201 (2.85%)
2 year	478 (0.17%)	4,895 (1.70%)	5,373 (1.87%)
1 year	204 (0.7%)	2,220 (0.70%)	2,424 (0.84%)

Note: The number and percentage of accounts of companies which will file for protection under Chapter 7 and 11 in 1, 2, 3, 4 and 5 year, i.e. with the horizon 1, 2, 3, 4 and 5 years.

matching the monthly frequency of patent submission data described in the next section.

After assigning the report time stamp to each account of companies, companies that are approaching the state of bankruptcy are defined. Credit event data in the database is reported based on the date (month and year) on which the default is filed by a firm. Each financial account of a such firm receives the default indicator $y = 1$ if the firm files for bankruptcy under Chapter 7 or 11 within the next 5 years cumulative from the date of the financial report (defaulting firms). The rest (non-defaulting firms) receive the default indicator $y = 0$. This horizon design is commonly used by credit rating agencies for assessing creditworthiness of a five years bond. This is also popular since the majority of corporate derivatives such as CDS are issued with the maturity of 5 years. However, in order to analyse the term structure of PD, default indicators for other horizons of one, two, three and four years cumulative are also constructed. It is also made sure that all insolvent firms exit the database after defaulting.

The number of accounts for companies that filed for bankruptcy in the data set for cumulative horizon is reported in Table 3.1 and it ranges from 0.84% for 1 year to 4.5% for 5 years.

3.3.2 Patent Data

The second source of information is a patent database provided by the European Patent Office (EPO) that covers around 98% of all primary patent applications in the world. This patent allows tracking patent applications submitted by US firms to around 90 patent offices golabally and include patent statistics from 1990 to 2008. The wide coverage of the data make it possible to track all patent filing of US companies worldwide, not only in the US.

Despite the availability of patent information from patent offices, its efficient use in research is considerably limited. The reason is that the names and addresses of patent applicants, assignees and inventors are not standardized. This does not allow for direct merging of patent data with other types of data on firms' performance. Therefore, when merging this data with other data sources based on the name of firms extra care should be taken. This becomes an issue since the same firm can be registered in different patent offices with different names, for instance a firm may appear as GM or General Motor or GM Inc.

In this study we use different forms of company names that can appear in the patent database to merge it with the financial accounting data. After the initial merging using the name from the financial accounts, an exhaustive manual check is performed for different alternative spelling and naming conventions. Companies that have successfully filed at least for one patent application in the past, receive the patent indicator 1 otherwise 0 in the merged database. The date of the first patent application is also recorded.

The merged database, including both patent information and the accounting information, contains 285,481 accounts (10,646 firms) for US firms from which 1,457 (13.69%) firms have had at least one patent application. This corresponds to 80,439 (28.17%) of accounts.

More details about distribution of patenting and defaulting firms in the data set are provided in Table 3.2. The last row in each table indicates the distribution of patenting firms among defaulting and non-defaulting firms and corresponding accounts. What is striking is that only 3.91% of the firms are defaulted from those who filed at least one patent application by the time of default.

Table 3.2: The distribution of patent applications among defaulted and non-defaulted companies. Patent indicator is “1” if at least one patent application had been filed prior to the reporting date, otherwise 0.

Number of accounts		
Patent	Non-defaulting	Defaulting
0	194,715 (68.20%)	10,327 (3.62%)
	(94.96%)	(5.04%)
1	77,727 (27.23%)	2,712 (0.95%)
	(96.63%)	(3.37%)

Number of firms		
Patent	Non-defaulting	Defaulting
0	8,823 (82.88%)	366 (3.44%)
	(90.25%)	(9.75%)
1	1,400 (13.15%)	57 (0.54%)
	(96.09%)	(3.91%)

3.3.3 Variable Description

This section provides detailed information about the explanatory variables used for the bankruptcy analysis in this study. In the literature, various accounting ratios have been introduced as main predictors of the credit risk of firm. These accounting ratios are mostly proxies for either profitability, liquidity, leverage, size or coverage as different aspects of firm performance. In this study, we use a range of accounting ratios that according to the existing literature are the best proxies compared to alternatives for each aspects of firm performance (Ohlson, 1980; Campbell et al., 2008; Duan et al., 2012). Table 3.3 contains a list of the variables along with their classification and definition.

In addition to the accounting ratios, we also investigate stock returns and stock price volatility as market driven forward looking predictors of risk. In our analysis the stock return variable (Exc Return) is calculated as the return over the average price one month before and after the date of the financial report. This return is then benchmarked against the market return. Stock price volatility (Stock Vol) is calculated as volatility of the price over one month before and after the date of the financial report.

These market variables have been suggested in previous studies as being strongly related to probability of bankruptcy (Shumway, 2001; Campbell et al., 2008; Löffler and Maurer, 2011).

In order to account for the impact of each variable on bankruptcy in different sectors, a set of dummy variables for each sector in which each firm operates is defined. The sectors are defined according to the Bloomberg industry classification system, provided in the RMI database. Altogether we distinguish between nine sectors, described in Table 3.3.

In order to investigate the impact of innovation and patenting on the probability of bankruptcy we introduced a dummy variable for a patent application in our analysis. To create the patent indicator dummy, date of the patent application is compared with date of the financial report. If a company has filed at least one patent application prior to the financial report date patent dummy receives 1 (Patent = 1) if not patent dummy receives 0 (Patent = 0).

3.3.4 Summary Statistics

A summary statistics of the variables for the firms who filed at least one patent and those who did not is provided in Table 3.4. As it is evident from the table, the performance of firms with patent is generally better than those without patent. The analysis of the summary statistics suggests that: (i) patenting firms have a higher profitability based on different metrics. For example, the median of NI/TA for patenting firms is higher than the median of NI/TA for non-patenting firms. (ii) the leverage is lower for patenting firms which presumably reveals their lower credit risk. Also, as the mean for OENEG is higher for the non-patenting firms, this suggests that a larger number of non-patenting firms suffer their total liabilities exceeding total assets, which technically constitutes distress. (iii) liquidity ratios, in particular the median of CASH/TA and WC/TA, are higher for patenting firms. (iv) larger firms in terms of their total assets seem more likely to apply for a patent.

Table 3.3: Variable Description

Variable	Description
	Profitability
NI/TA	Return on assets: net income / total assets
INTWO	1 if net income was negative for the last two years, 0 otherwise
CHIN	Measure of change in net income: $(NI_t - NI_{t-1})/(\lvert NI_t\rvert) + (\lvert NI_{t-1}\rvert)$
FU/TL	Fund from operations / total liabilities
	Leverage
TD/TA	Bank debt ratio: total bank debt / total assets
OENEG	1 if total liabilities exceed total assets, 0 otherwise
	Liquidity
CASH/TA	Cash and cash equivalents / total assets
WC/TA	Working capital ratio: (current assets - current liabilities)/ total assets
CL/CA	Current ratio: current liabilities / current assets
	Size
Log TA	Company size: Logarithm of total assets
	Market
Exc Return	Excess returns: monthly stock returns - monthly S&P returns
Stock Vol	Monthly stock price volatility
	Patent Indicator
Patent	1 if a firm files at least one patent application prior to the date of financial report, 0 otherwise
	Sector Indicators
D1, D2, D3, D4, D5, D6, D7, D8, D9.	Basic Materials, Communications, Consumer Cyclical, Consumer Non-cyclical, Diversified, Energy, Industrial, Technology, Utilities. 1 for the respective sector, otherwise 0

(v) interestingly, excess returns are also higher for the patenting firms than non-patenting firms, though, stock price volatility is higher for patenting firms. (vi) the standard deviation of all predictors, except for INTWO, FU/TL, CASH/TA and Stock Vol, are larger for non-patenting firms compared to patenting firms.

Table 3.5 provides a comparison of the summary statistics for non-defaulting and defaulting firms (companies that will default within five years) and also for patenting and non-patenting firms. As the table shows majority of the ratios deteriorate when moving from patenting to non-patenting group and also when moving from non-defaulting to defaulting firms.

Similar differences between patenting and non-patenting firms have been identifiable between non-defaulting and defaulting firms. For example, patenting firms are less leveraged than the non-patenting firms and a similar difference is shown between the non-defaulting and defaulting firms. In other words, both patenting and non-defaulting firms, on average, indicate higher profitability, liquidity and lower leverage ratios compared to the non-patenting and defaulting firms.

Also, in order to analyse the differences between the patenting and non-patenting firms as well as the differences between the non-defaulting and defaulting firms, a mean comparison for each variable between each two groups are provided in the last column of each section of the Table 3.5. As the results indicate mean values of all variables for patenting firms are significantly different from those for non-patenting firms. Similar results are obtained between the non-defaulting and defaulting firms. As expected in the majority of ratios, the non-patenting firms have lower profitability and liquidity as well as higher leverage ratios compared to the patenting firms. The similar pattern is observed between non-defaulting and defaulting firms. Overall, the results from the mean comparison analysis suggest that the set of explanatory variables applied in this study might help to explain why some firms default.

Table 3.4: Summary statistics of accounting and market variables used for bankruptcy analysis for US firms that had applied for a patent and those that had not.

	Non-Patenting Firms							Patenting Firms						
Variable	Min	$q_{0.05}$	Mean	Med	$q_{0.95}$	Max	SD	Min	$q_{0.05}$	Mean	Med	$q_{0.95}$	Max	SD
Profitability														
NI/TA	-0.462	-0.276	-0.028	0.006	0.050	0.094	0.106	-0.462	-0.216	-0.023	0.007	0.048	0.094	0.094
INTWO	0.000	0.000	0.105	0.000	1.000	1.000	0.307	0.000	0.000	0.153	0.000	1.000	1.000	0.360
CHIN	-1.000	-1.000	-0.014	0.000	1.000	1.000	0.595	-1.000	-1.000	0.001	0.000	1.000	1.000	0.554
FU/TL	-0.685	-0.475	-0.010	0.017	0.284	0.461	0.205	-0.685	-0.599	-0.014	0.023	0.318	0.461	0.227
Leverage														
TD/TA	0.000	0.000	0.262	0.223	0.790	0.790	0.235	0.000	0.000	0.193	0.137	0.634	0.790	0.206
OENEG	0.000	0.000	0.093	0.000	1.000	1.000	0.291	0.000	0.000	0.058	0.000	1.000	1.000	0.234
Liquidity														
CASH/TA	0.002	0.002	0.112	0.049	0.498	0.521	0.142	0.002	0.004	0.149	0.090	0.521	0.521	0.155
WC/TA	-0.390	-0.390	0.196	0.184	0.704	0.729	0.284	-0.390	-0.103	0.316	0.312	0.729	0.729	0.263
CL/CA	0.119	0.129	0.783	0.576	2.639	2.639	0.658	0.119	0.119	0.541	0.423	1.381	2.639	0.464
Size														
Log TA	0.884	0.884	4.587	4.536	8.538	8.802	2.195	0.884	1.705	5.285	5.219	8.802	8.802	2.102
Market														
Exc Return	-1.015	-0.351	0.003	-0.029	0.368	69.795	0.523	-0.958	-0.318	0.005	-0.018	0.344	59.240	0.430
Stock Vol	0.000	0.001	0.728	0.164	3.757	5.832	1.259	0.000	0.003	1.107	0.370	5.002	5.832	1.559

Note: $q_{0.05}$, $q_{0.95}$, Med and SD are respectively 5% quantiles, 95% quantiles, median and standard deviation.

Table 3.5: Comparison of summary statistics of financial and market variables, for patenting and non-patenting companies, and also for non-defaulting and defaulting companies.

	Patenting					Defaulting				
	Patent=1		Patent=0		t statistics	y=0		y=1		t statistics
Variable	Mean	SD	Mean	SD	Mean diff. test	Mean	SD	Mean	SD	Mean diff. test
Profitability										
NI/TA	-0.023	0.094	-0.028	0.106	-10.24***	-0.024	0.101	-0.066	0.124	47.44***
INTWO	0.153	0.360	0.105	0.307	-35.46***	0.114	0.318	0.211	0.408	-32.06***
CHIN	0.001	0.554	-0.014	0.595	-5.88***	-0.011	0.583	0.033	0.606	-7.58***
FU/TL	-0.014	0.227	-0.010	0.205	3.68***	-0.009	0.212	-0.063	0.188	31.64***
Leverage										
TD/TA	0.193	0.206	0.223	0.235	72.65***	0.236	0.226	0.375	0.262	-73.97***
OENEG	0.058	0.234	0.093	0.291	30.75***	0.078	0.268	0.229	0.421	-47.63***
Liquidity										
CASH/TA	0.149	0.155	0.112	0.142	-61.61***	0.124	0.147	0.093	0.132	23.68***
WC/TA	0.316	0.263	0.196	0.284	-103.65***	0.236	0.282	0.102	0.291	51.23***
CL/CA	0.541	0.464	0.783	0.658	95.82***	0.703	0.609	0.982	0.754	-49.74***
Size										
Log TA	5.285	2.102	4.587	2.195	-77.58***	4.787	2.201	4.820	2.062	4.00***
Market										
Exc Return	0.005	0.430	0.003	0.523	-0.86	0.006	0.487	-0.037	0.672	10.47***
Stock Vol	1.107	1.559	0.728	1.259	-65.92***	0.852	1.371	0.516	1.131	24.82***

Note: A t-test for mean comparison is performed which examines the null hypothesis that the means of the two groups are equal. The mean comparison is a t-test using the Cochran and Cox approximation to account for possible unequal variances between the two groups. The last column in each group reports the results of this test for the patent and non-patenting firms and for the defaulting and non-defaulting firms. ***, ** and * represent 1%, 5% and 10% significance level respectively.

3.3.5 Pairwise Correlation

For the purpose of variable diagnostics we perform a pairwise correlation analysis among the covariates used in the study for which the results are reported in Table 3.6. The degree of correlation varies significantly between the variables. The highest relationship is the negative correlation observed between WC/TA and CL/CA ($\rho = -0.75$) and the smallest is between excess return and TL/TA ($\rho = 0.00$).

Generally, excess returns display the lowest degree of correlation with other variables, not exceeding $|\rho| = 0.03$, which indirectly confirms the hypothesis of market inefficiency.

According to Kennedy (2008), the OLS estimators suffer from multicollinearity if the correlation is equal to or greater than 0.8. Despite the large variation among the correlations reported in Table 3.6, all coefficients are below 0.8 and multicollinearity is not an issue here.

Table 3.6: Pearson correlation coefficients between accounting and market variables.

Variable	NI/TA	TD/TA	CL/CA	CASH/TA	Log TA	WC/TA	FU/TL	chin	Excess-Return	Stock Vol
NI/TA	1									
TD/TA	-0.31	1								
CL/CA	-0.35	0.65	1							
CASH/TA	-0.19	-0.28	-0.28	1						
Log TA	0.41	-0.01	-0.14	-0.27	1					
WC/TA	0.24	-0.68	-0.75	0.45	-0.04	1				
FU/TL	0.46	0.01	0.00	-0.20	0.27	-0.09	1			
chin	0.04	0.07	0.07	0.05	-0.09	-0.05	-0.05	1		
Excess-Return	0.03	0.00	-0.01	0.02	-0.02	0.01	0.01	0.03	1	
Stock Vol	0.19	-0.14	-0.15	0.03	0.40	-0.11	0.14	-0.05	0.01	1

Note: The low correlation between excess returns and other vatiables below $|\rho| = 0.03$ confirms the hypothesis of market inefficiency.

3.4 Methodology

Logistic models are commonly applied by researchers and practitioners to evaluate the impact of various credit risk factors on the probability of default (PD). The corporate finance literature features two popular approaches to measure the PD based on logistic estimators: the first approach uses a pooled logistic estimator over a period of time (see e.g. Carey and Hrycay, 2001; Campbell et al., 2008; Modina and Pietrovito, 2014), while the second approach considers a specific point in time to apply a static logistic estimator (Ohlson, 1980). Both approaches can estimate the PD based on a combination of accounting and market indicators. In addition, to investigate if the impact of the PD determinants on the PD varies over time, it is a common practice to calibrate logistic models at different horizons before bankruptcy (Campbell et al., 2008). Nonetheless, this approach may not be very useful when the span of data is long. The main shortcoming of the logistic models is that they take no account of time in modeling corporate bankruptcy. Furthermore, another shortcoming of logistic models is that they take no account of firms that exit the sample for reasons other than bankruptcy, while this is a common phenomenon in corporate finance.

A popular approach to resolve these issues is to apply hazard models, which account for time. Hazard models are commonly used to model the time it takes for a firm to go bankrupt. In this context, financial strength of a firm changes through time, and it is a function of its latest financial information. Hazard models are also able to account for firms that leave the data set for reasons other than bankruptcy such as delisting or merger and acquisition. Such firms are treated as censored observations in the hazard models. Another advantage of the hazard models is that they capture the time variation of explanatory variables. If financial health of a firm deteriorates before bankruptcy, it is important to allow its financial information to unfold this deterioration (Shumway, 2001). Therefore, it is not surprising that the number of studies that use various forms of hazard models in bankruptcy analysis has increased substantially over the last few decades. In this study, following Bellotti and Crook (2009) and Im et al. (2012), we apply a Cox (1972) proportional hazard model, with time varying covariates, to investigate the impact of technological activities as well as accounting and market indicators on the timing of bankruptcy of US publicly listed firms over the period 1980 to 2010. In this section, we briefly present the Cox proportional hazard model.

Let T_i be the time until firm i defaults, implying that firm i operates at J_i distinct quarters under the risk of default: $t_{i1} < t_{i2} < ... < t_{iJ_i} < T_i$. Note that in this study firm default is defined as firm exit due to filing for bankruptcy under Chapter 7 or 11 of the US bankruptcy law. Since T_i is a random variable, its cumulative distribution function (CDF) is defined as

$$P_i(t) = Pr(T_i \leq t) \tag{3.4.1}$$

The CDF of T_i represents the probability that the ith firm defaults before a specific time t, meaning that $T_i \leq t$. Similarly, the probability density function (pdf) of T_i is given by

$$p_i(t) = dP_i(t)/dt \tag{3.4.2}$$

In survival analysis, however, the object of primary interest is the survivor function, $S_i(t)$, which is the complement of the CDF. The survivor function is defined as

$$S_i(t) = Pr(T_i > t) = 1 - P_i(t) \tag{3.4.3}$$

For its estimation, it is a common practice to use a related terminology known as a hazard function, $h(t)$, which is defined as

$$h(t) = \lim_{dt \to 0} \frac{Pr(t \leq T_i < t + dt | T_i \geq t)}{dt} = \frac{p_i(t)}{S_i(t)} \tag{3.4.4}$$

In other words, the hazard function is the instantaneous risk of a firm defaulting at time t, conditional upon not having defaulted up to time t. Cox (1972) proposes the following specification for the hazard function.

$$h_i(t|x_i(t)) = h_o(t)\exp(x_i(t)\beta) \tag{3.4.5}$$

In the above equation $x_i(t)$ is a $1 \times m$ vector of time varying covariates, β is an $m \times 1$ vector of coefficients, and $h_o(t)$ is the baseline hazard function. If a distributional assumption, e.g. of an exponential or Weibull distribution, is made for the baseline hazard function, this model becomes fully parametric. However, one advantage of the Cox model is that the baseline hazard function is unspecified. In this context, the Cox model is a semi-parametric model consisting of a parametric term, $\exp(x_i(t)\beta)$, and a non-parametric term, $h_o(t)$. Furthermore, the Cox model is a proportional hazard model, meaning that $h_o(t)$ is analogous for all firms at time t. Therefore, the relative hazard of two firms j and i at time t is given by

$$\frac{h_o(t)\exp(x_i(t)\beta)}{h_o(t)\exp(x_j(t)\beta)} = \frac{\exp(x_i(t)\beta)}{\exp(x_j(t)\beta)} \tag{3.4.6}$$

Cox (1972) proposes the method of partial likelihood to estimate equation (3.4.5). Let T_j, $j = 1, \ldots, D$ denote the ordered distinct default times, and let R_j be the set of all firms that are at risk of default at a time just before T_j. Accordingly, the partial maximum likelihood estimates are obtained by maximizing the Cox likelihood function[1]

$$L(\beta) = L_1(\beta)L_2(\beta)...L_D(\beta) = \prod_{j=1}^{D} \frac{\exp(x_j(T_j)\beta)}{\sum_{i\in R_j}\exp(x_i(T_j)\beta)} \tag{3.4.7}$$

or, its corresponding log likelihood function

$$l(\beta) = \sum_{j=1}^{D} l_j(\beta) = \sum_{j=1}^{D} \left[x_j(T_j)\beta - log\left(\sum_{i\in R_j}\exp(x_i(T_j)\beta)\right)\right] \tag{3.4.8}$$

Accordingly, $\hat{\beta}$ is obtained by solving the following equation

$$\frac{\partial l(\beta)}{\partial \beta} = \sum_{j=1}^{D}\left[x_j(T_j) - \frac{\sum_{i\in R_j}\exp(x_i(T_j)\beta)x_i(T_j)}{\sum_{i\in R_j}\exp(x_i(T_j)\beta)}\right] = 0 \tag{3.4.9}$$

[1]The Cox likelihood function is a partial likelihood function because it eliminates the quarters when no default is observed. However, a partial likelihood function can be treated as a complete likelihood function when making inference.

One critical assumption in the Cox model is that there are no tied [2] defaults in the data set, which is often violated in the empirical works. To resolve this issue, Breslow (1974) proposes the following approximation of the Cox partial likelihood function

$$L(\beta) = \prod_{j=1}^{D} \frac{\exp(x_i(T_j)\beta)}{\sum_{i\in R_j}\exp(x_i(T_j)\beta)} \approx \prod_{j=1}^{D} \frac{\exp(\sum_{i\in D_j} x_i(T_j)\beta)}{\left[\sum_{i\in R_j}\exp(x_i(T_j)\beta)\right]^{d_j}} \tag{3.4.10}$$

In this function, d_j represents the total number of tied defaults and D_j is the number of tied defaults at time T_j. This approximation performs very well if the number of defaults is relatively small compared to the number of survived firms at each quarter.

Another challenge in the survival analysis is to account for the correlation in the performance of firms operating within a specific sector. The correlation may be attributed to some overall industry characteristics that remain unobserved. In this context, a further generalization of the Cox model exits which is known as a shared frailty Cox model. Let n denote the total number of firms and n_k represent the number of firms operating in the kth sector. The Cox hazard model with shared frailty is specified as

$$h_{ik}(t|x_{ik}(t), \alpha_k) = \alpha_k h_o(t)\text{exp}(x_{ik}(t)\beta) \tag{3.4.11}$$

Where a shared frailty α_k is assumed to follow a gamma distribution $g(\alpha_k)$ with mean one and variance θ, specified as follows

$$g(\alpha_k) = \frac{\alpha_k^{1/\theta-1} exp(-\alpha_k/\theta)}{\Gamma(1/\theta)\theta^{1/\theta}} \tag{3.4.12}$$

In fact, the shared frailty models are analogous to random-effects regression models as α_k affects the hazard multiplicatively. Furthermore, the frailties are shared across groups of firms operating in the same sectors rather than being firm

[2]Tied default means that there are more than one default at the time T_j.

specific. In other words, using the shared frailty models, it is assumed that each firm shares the same frailty with other firms operating in the same sector.

Overall, the main advantage of applying the partial likelihood for estimating a hazard function is that it accounts for potential endogeneity of time varying covariates with respect to default times. Additionally, the Cox proportional hazard model, unlike parametric models, makes no arbitrary and possibly incorrect assumption about the form of the baseline hazard function. Nonetheless, the estimates of β are more efficient if the shape of the baseline hazard is accurately specified. More specifically, there is a trade-off between efficiency and making an assumption for the baseline hazard.

3.5 Empirical Results

In this section we present the empirical results of estimating the Cox proportional hazard regressions with time-varying covariates for modeling the factors affecting the survival time of the US firms with the main focus on the impact of patent application.

In this study, the estimated coefficient are reported instead of the hazard ratios. However, the hazard ratio of a covariate can be computed by exponentiating its estimated coefficient. The exponentiated coefficient indicates the respective change in failure hazard due to a one unit change in the covariate, keeping all other covariates constant. A negative coefficient means that an increase of the corresponding covariate reduces the failure hazard and increases the likelihood of survival, while a positive coefficient indicates that an increase in the relevant covariate increases the failure hazard. Also, for each regression, the likelihood χ^2 statistic, Wald test and pseudo R-squared statistics are reported to evaluate its goodness of fit and the overall statistical significance.

3.5.1 Credit Default and Time Structure of Default

Table 3.7 presents the estimated results for the time-to-failure hazard model as specified in (3.4.5) (see also equation 3.4.9), with l=5 referring to bankruptcy within the next 5 years. In this table, five models as various alternative specifications are presented with the variable "patent" as the main variable in all of them. Model 1, contains only the accounting indicators mainly applied by (Ohlson, 1980; Becchetti and Sierra, 2003) as well as the patent indicator. Model 2 involves the same variables from model 1 whilst adding sector dummies. Model 3 includes accounting and also market variables mainly from (Campbell et al., 2008) which are also applied in other studies (such as Shumway, 2001; Löffler and Maurer, 2011; Duan et al., 2012), as well as the patent indicator. Also, within this setting, model 4 adds sector dummies to the accounting and market indicators from model 3. Model 5 includes a combination of the accounting indicators from model 1 and 3 in such a way that one indicator from each main group of accounting indicators is included in the model. Model 5 also considers the patent indicator, which is the main variable, as well as the market indicators and the sector dummies. The forementioned model specifications are the basis of the analysis in the rest of the chapter, unless otherwise specified.

In general, the empirical results reported in Table 3.7 indicate that all accounting ratios except WC/TA, Log TA and INTWO have significant impact on survival likelihood of firms. These results are robust in terms of the sign across all the models, however, the magnitude of significance varies slightly for some covariates.

Profitability seems to be an important contributor in explaining why some firms might default, exhibiting negative and statistically significant coefficients for NI/TA and FU/TL across all models. As expected, more profitable firms have a better financial position, hence lower probability to default. Many other studies (for instance Shumway, 2001; Pederzoli et al., 2013) also confirm the same results for profitability. Positive sign obtained for CHIN contrary to the results in Franzen et al. (2007) can have the only possible explanation proposed by Ohlson (1980). This is that firms with a positive change in earnings may be particularly tempted to raise external financing and this will then imply that they become higher risk firms at a subsequent point. Similar to the results obtained by Ohlson (1980), INTWO is not a significant factor in explaining default probability, however, Franzen et al. (2007) report a positive correlation between INTWO and higher probability of default.

The main leverage indicator, which is defined as the ratio of total debt to total assets, TD/TA, also suggests that firms with healthier financial position are more likely to survive longer than the firms with a higher weight of debt.

Moreover, the liquidity ratios also have a negative impact on the survival of firms, implying that firms facing more constrained liquidity positions may have more difficulties in meeting their debt commitments. The expected impact of CASH/TA reducing bankruptcy hazard in models 3, 4 and 5 is consistent with the results reported by Carey and Hrycay (2001), Becchetti and Sierra (2003), Bonfim (2009) and Duan et al. (2012).

In this study, firm size, which is defined as a logarithm of total assets, has no significant impact on firm survival. However, the exception is the first model, where the firm size impact is significant at 10% significance level with a positive sign, which is contrary to the expected negative sign. It can be argued that other models do not support this finding, and also it is significant only marginally with a p-value of 0.098. Campbell et al. (2008) also find a positive relationship between size and probability of default which is not also robust in all of their models. Simiarly, market variables, i.e. excess returns and return volatility, are not significant predictors of default for five year horizon, which is consistent with the results obtaind by Löffler and Maurer (2011).

Furthermore, results from Table 3.7 show that compared to the firms in the basic materials industry, firms operating in consumer cyclical industry (D3) face higher probability of default and those operating in consumer non-cyclical (D4), energy (D6), technology (D8) and utilities (D9) are less likely to default.

Patenting as an output indicator of R&D investments and technology focused innovations can explain the reduction in the future financial distress rates and the likelihood of bankruptcy. The negative coefficients, as expected and consistent across all models, and the low p–values confirm that patent provides additional information over typical bankruptcy prediction measures for bankruptcy prediction. In fact, firms with a superior position in technological development and technology competition survive longer in terms of financial stability.

The results are consistent with the intuition obtained from the literature. Considering the fast growing technological environment, firms with no patenting activities experience harsher technology completion and are more likely to face financial distress because of extreme market competition and potential costly patent litigations. Consistent with the findings by Eisdorfer and Hsu (2011), firms are more likely to default if they are incapable of catching up with their rivals in patenting competition.

Table 3.7: Bankruptcy hazard model coefficients for US firms.

	1		2		3		4		5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.105	(0.324)	-0.109	(0.326)	-0.838***	(0.271)	-0.898***	(0.273)	-1.137***	(0.316)
TD/TA	2.031***	(0.176)	1.913***	(0.175)	0.635***	(0.111)	0.602***	(0.111)	0.808***	(0.144)
CL/CA	-0.278**	(0.114)	-0.303***	(0.113)	.	.	.	.	.	.
WC/TA	-0.170	(0.246)	-0.307	(0.247)	.	.	.	.	.	.
Log TA	0.027*	(0.016)	0.018	(0.016)	.	.	.	.	0.009	(0.019)
CASH/TA	.	.	.	.	-0.574**	(0.239)	-0.449*	(0.247)	-0.653**	(0.264)
OENEG	-0.865***	(0.160)	-0.842***	(0.157)	.	.	.	.	.	.
FU/TL	-1.705***	(0.166)	-1.702***	(0.166)	.	.	.	.	.	.
INTWO	-0.165	(0.115)	-0.139	(0.115)	.	.	.	.	.	.
CHIN	0.134***	(0.052)	0.145***	(0.051)	.	.	.	.	.	.
Patent	-0.241***	(0.083)	-0.166**	(0.084)	-0.203**	(0.091)	-0.154*	(0.092)	-0.178*	(0.093)
D2	.	.	0.267*	(0.162)	.	.	0.079	(0.174)	0.091	(0.173)
D3	.	.	0.336**	(0.160)	.	.	0.278*	(0.167)	0.264	(0.167)
D4	.	.	-0.399**	(0.165)	.	.	-0.394**	(0.171)	-0.397**	(0.170)
D5	.	.	-0.049	(0.481)	.	.	-0.381	(0.525)	-0.354	(0.526)
D6	.	.	-0.390*	(0.209)	.	.	-0.435**	(0.211)	-0.384*	(0.210)
D7	.	.	-0.194	(0.167)	.	.	-0.245	(0.173)	-0.258	(0.173)
D8	.	.	-0.524***	(0.185)	.	.	-0.553***	(0.194)	-0.548***	(0.194)
D9	.	.	-1.565***	(0.438)	.	.	-2.352***	(0.600)	-2.319***	(0.603)
Exc Return	.	.	.	.	0.032	(0.022)	0.028	(0.023)	0.030	(0.022)
Stock Vol	.	.	.	.	-0.031	(0.031)	-0.042	(0.031)	-0.048	(0.034)
No. observations	269,868		269,868		256,644		256,644		256,644	
No. fail	1043		1043		913		913		913	
No. firms	10468		10468		10216		10216		10216	
Wald test	353.4		488.1		158.5		259.7		266.1	
Pseudo-R^2	0.164		0.236		0.0675		0.138		0.142	
LogL	-9025		-8958		-7899		-7843		-7840	

Note: All coefficients are estimated for the Cox proportional hazard model with time varying covariates. The dependent variable is a bankruptcy dummy, that is 1 if a firm files for bankruptcy under Chapter 7 or 11 within 5 years and 0 otherwise. The pseudo R^2 is a measure of goodness of fit comparing the log-likelihood of the estimated model with the log-likelihood of a constant-only model. The Wald test analyses the overall significance of the estimated coefficients. SE represents robust standard errors which accounts for the possible presence of heteroscedasticity. ***, ** and * indicate 1%, 5%, 10% significance levels, respectively.

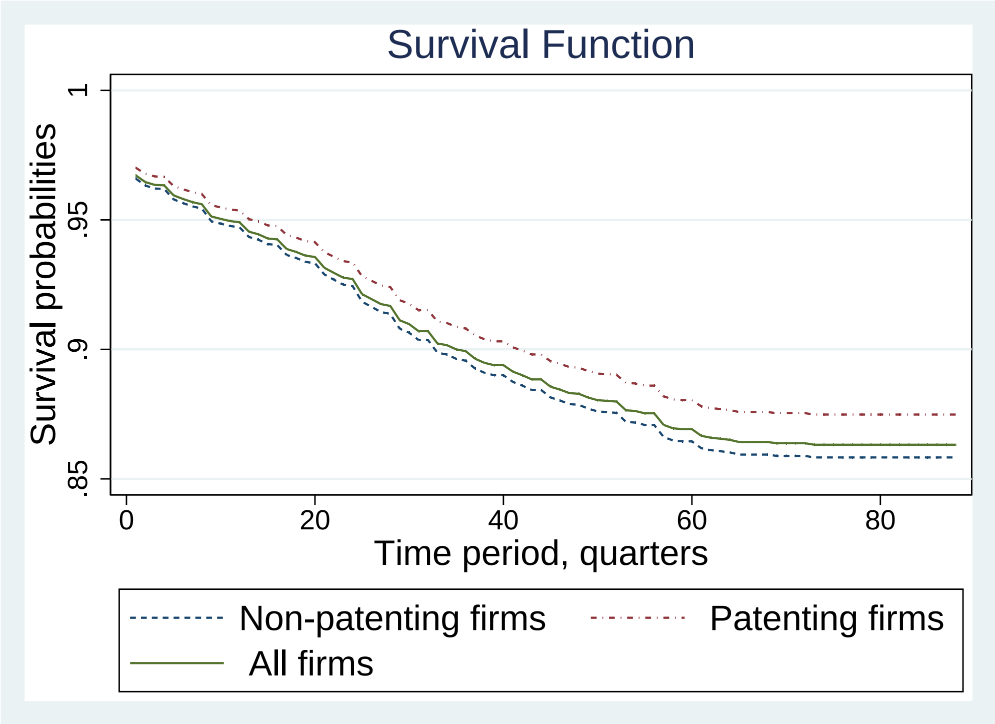
Figure 3.1 represents the estimated survival function based on the Cox proportional hazard model. This describes the probability of surviving after a certain amount of time. The estimated survival functions are produced for all covariates at their average values. The figure shows the survival function based on the entire data set and the survival functions for the patenting and non-patenting firms separately. The fact that the probability of surviving over longer periods declines is consistent with the intuitive assumption of the Poisson distribution of survival times. Patenting firms have a higher probability of surviving compared to the non-patenting firms for the same time period. This supports the view given by the initial argument that patent applications have a positive impact on firms' financial performance and reduce the probability of experiencing financial distress for all periods.

Additionally, Figure 3.2 reports the estimated hazard function based on the Cox proportional hazard model. This describes the relative likelihood of bankruptcy occurring at a certain time, conditional on the survival up to that time. The hazard rate, therefore, describes the instantaneous rate of default at a certain time. Similar to the survival function, the hazard functions are produced for all covariates at their average values. The hazard rate, similarly to the survival function, is declining over time as well as being lower for patenting compared to non-patenting firms for the same period.

Next, we investigate and compare the impact of the covariates on time-to-failure within the horizons of 1, 2, 3, 4 and 5 years. Table 3.8 reports the estimation results for model 5 from Table 3.7 as the basis which contains at least one variable from each financial group and market indicators, as well the patent and sector dummies.

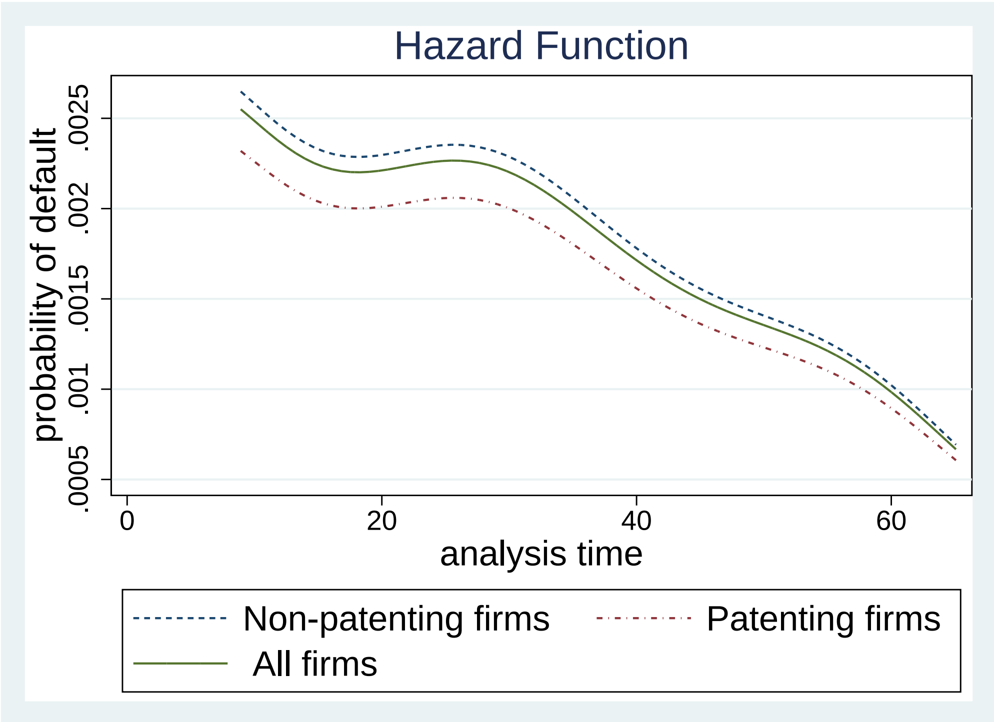
As expected, with an increase in the horizon, the coefficients and significance level of the accounting variables and the general fit of the models decline. However, most of the variables remain statistically significant with the expected sign, except for Log TA which shows a positive relationship with default probability. Excess return exhibits a negative relationship with default, significant only for a 1 year horizon. This suggests that the excess return variable is a primarily short-term financial distress predictor, which has also been confirmed by Campbell et al.

Figure 3.1: the survival function based on the Cox proportional hazard regression for the whole data set, patenting and non-patenting firms separately.



Note: The survival rate declines over the time. Moreover, survival rate is higher for the patenting firms. The survival rate is 94% (after 20 quarters or 5 years) and 91% (after 40 quarters or 10 years) for patenting firms, whereas the survival rate is 93% and 88% for non-patenting firms for the same period, respectively.

Figure 3.2: Smoothed hazard function based on the Cox proportional hazard regression for the whole data set, patenting and non-patenting firms separately.



Note: The hazard rate declines over time. Moreover, hazard is lower for the patenting firms. The hazard rate is 0.20% (20 quarters or 5 years) and 0.16% (40 quarters or 10 years) for patenting firms, whereas it is 0.23% and 0.18% for non-patenting firms for the same periods, respectively.

(2008).

The impact of the sectors on default prediction is diverse. The communication and consumer cyclical sector dummies (D2 and D3) have a significantly higher PD for the 1 and 2 year horizon. This significance goes down as the horizon increases until the effect becomes insignificant for a 5 year horizon. However, the technology sector (D8) has a negative and significantly lower PD for longer term bankruptcy prediction and utilities (D9) display a lower PD across all horizons. For all specifications the basic materials sector was used as a reference.

The most revealing results are related to the patent indicator. Patent applications have a negative correlation with bankruptcy which becomes significant for 2, 3, 4 and 5 years horizon. In addition, the highest significance of patent applications for bankruptcy prediction is observed for the prediction within 3 or 4 year horizon. Both results are consistent with the time lag between the date of the priority application and disclosure of a patent. Since a patent application is disclosed to public 18 months after the priority date, implicit benefits of the application are expected to become revealed and priced in after these 18 months. This is also evident from the highest coefficient reducing PD for horizons 3 and 4 year.

In cases that the patent application is successful and patent is granted, the above argument becomes stronger as it usually takes about 3 or 4 years for an application to be examined, processed and the patent granted. Therefore, the 3 or 4 years expected period which is needed for a patent to be realized, supports this argument. The longer time of 5 years to incorporate the impact of patent application into financial performance of a firm, can be due to the technological complexity of the innovation, greater initial market confrontation or longer required administrative processes.

Table 3.8: Bankruptcy hazard model coefficients for US firms for 1 - 5 years prediction horizon which uses the variables from model 5 in Table 3.7.

Bankruptcy horizon	(1 year)		(2 years)		(3 years)		(4 years)		(5 years)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-2.596***	(0.358)	-2.109***	(0.309)	-1.562***	(0.322)	-1.158***	(0.307)	-1.137***	(0.316)
TD/TA	1.489***	(0.163)	1.360***	(0.152)	1.002***	(0.152)	0.829***	(0.145)	0.808***	(0.144)
Log TA	0.257***	(0.019)	0.114***	(0.018)	0.050***	(0.018)	0.037**	(0.018)	0.009	(0.019)
CASH/TA	-1.478***	(0.331)	-0.770***	(0.273)	-0.554**	(0.266)	-0.135	(0.256)	-0.653**	(0.264)
Exc Return	-1.627**	(0.776)	-0.106	(0.219)	-0.181	(0.195)	-0.046	(0.074)	0.030	(0.022)
Stock Vol	-0.596***	(0.089)	-0.121***	(0.038)	-0.013	(0.031)	-0.065*	(0.033)	-0.048	(0.034)
Patent	-0.106	(0.089)	-0.162*	(0.085)	-0.208**	(0.088)	-0.209**	(0.090)	-0.178*	(0.093)
D2	0.455***	(0.176)	0.479***	(0.171)	0.297*	(0.170)	0.194	(0.171)	0.091	(0.173)
D3	0.426**	(0.171)	0.396**	(0.169)	0.317*	(0.167)	0.296*	(0.166)	0.264	(0.167)
D4	-0.118	(0.174)	-0.168	(0.171)	-0.297*	(0.170)	-0.358**	(0.170)	-0.397**	(0.170)
D5	-0.890	(0.715)	-0.210	(0.531)	-0.578	(0.598)	-0.631	(0.599)	-0.354	(0.526)
D6	-0.160	(0.212)	-0.115	(0.207)	-0.279	(0.208)	-0.394*	(0.211)	-0.384*	(0.210)
D7	-0.076	(0.178)	-0.134	(0.175)	-0.210	(0.174)	-0.262	(0.173)	-0.258	(0.173)
D8	-0.244	(0.203)	-0.250	(0.193)	-0.413**	(0.192)	-0.492**	(0.191)	-0.548***	(0.194)
D9	-2.313***	(0.481)	-2.004***	(0.480)	-2.433***	(0.601)	-2.411***	(0.602)	-2.319***	(0.603)
No. observations	266,318		263,595		260,997		258,699		256,644	
No. fail	906		986		967		939		913	
No. firms	10399		10369		10314		10258		10216	
Wald test	1356		816.8		464.4		326.1		266.1	
Pseudo-R^2	0.0854		0.0334		0.0201		0.0161		0.142	
LogL	-7143		-8254		-8221		-8032		-7840	

All coefficients are estimated for the Cox proportional hazard model with time varying covariates. The dependent variable is a bankruptcy dummy, that is 1 if a firm files for bankruptcy under Chapter 7 or 11 within 1 - 5 years respectively and 0 otherwise. The pseudo R^2 is a measure of goodness of fit comparing the log-likelihood of the estimated model with the log-likelihood of a constant-only model. The Wald test analyses the overall significance of the estimated coefficients. SE represents robust standard errors which accounts for the possible presence of heteroscedasticity. ***, ** and * indicate 1%, 5%, 10% significance levels, respectively.

3.5.2 Robustness Check

In this section, we conduct robustness checks of the results reported in the previous sections. For this purpose, the same model specifications from Table 3.7 are estimated for three sub samples that are based on the size of the firms. The data set has been split into three sub-samples of small, medium and large firms, based on the quartiles of total assets. The small firms are from the first quartile of the distribution, the medium firms are from the second and third quartiles and the large firms are from the fourth quartile. The results of the analysis of different firm size groups are reported in Tables 3.9, 3.10 and 3.11.

The results indicate that the profitability and leverage indicators perform similarly for small, medium and large firms across the models. The only difference is that the leverage is a significant predictor for bankruptcy for small firms only for the the shorter horizons of 1, 2 and 3 years and liquidity, defined by CASH/TA, is a poor predictor of bankruptcy of small firms. WC/TA is significant and shows the expected negative sign for the medium size firms. Size, Log TA, is significant only for large firms with the expected negative sign as also reported by Ohlson (1980), Becchetti and Sierra (2003) and Löffler and Maurer (2011). Additionally, the INTWO variable only for the large firms, unlike the previous discussed results, has a positive and significant impact on the default probability, suggesting that the financial distress can be reflected in the deteriorating net income two years prior to bankruptcy.

Tables 3.9-3.11 indicate that the stock return volatility, Stock Vol, is an important indicator with positive and significant impact on bankruptcy only for small firms, indicating that smaller firms's bankruptcy is more sensitive to the market perceptions, rather than the medium or large firms. Also, excess stock returns variable, Exc Return, show a positive, though weak, significant effect on bankruptcy for medium size firms.

The expected positive impact of return volatility and the negative impact of stock return on bankruptcy is also confirmed by Campbell et al. (2008) and Löffler and Maurer (2011).

Differences across sectors do not seem to have effect on PD among small firms, however, the impact of all variables becomes more significant when shifting to medium and large firms.

As far as the results for patent application are concerned, filing for patent has no significant effect on PD for small firms, whereas it becomes significant when the firm size increases. As it can be seen from the Tables 3.9, 3.10 and 3.11, the patent dummy becomes a significant predictor of bankruptcy with the expected negative sign for medium and large firms. This can be due to the fact that small firms file fewer international patent applications than the large and multinational firms and also that patents filed by small firms are withdrawn more frequently (due to for example the relative high costs associated with processing the patent) compared to the patents filed by large firms (Frietsch et al., 2013). This is also evident in the data set used in this analysis. The patenting accounts of companies represent only 18% of all small firms accounts, compared to the 29.5% and 35.3% for the medium and large firms, respectively.

A major related point to take into account is that small firms, compared to their large counterparts, are more financially constrained and have less resources and market power to enforce their rights (Neuhäusler, 2012).

This result reveals that small firms, and to some extent medium ones, face more severe technological competition. The recent and rapid increase in the technological competition and the globalization of market power require more focus on patenting by firms internationally. One implication of this finding is that large firms with more profound technological capabilities often act more effectively for their technological developments, whereas small firms have potential for further developments (Frietsch et al., 2013).

Table 3.9: Bankruptcy hazard model coefficients for US small firms.

	1		2		3		4		5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-1.326***	(0.393)	-1.311***	(0.395)	-0.970***	(0.312)	-0.937***	(0.314)	-1.612***	(0.347)
TD/TA	0.898***	(0.291)	0.909***	(0.290)	0.231*	(0.133)	0.209	(0.135)	0.273	(0.215)
CL/CA	-0.129	(0.155)	-0.145	(0.153)	.	.	.	.	.	.
WC/TA	-0.591	(0.389)	-0.553	(0.389)	.	.	.	.	.	.
Log TA	0.506***	(0.075)	0.504***	(0.076)	.	.	.	.	0.568***	(0.075)
CASH/TA	.	.	.	.	-0.213	(0.291)	-0.165	(0.296)	0.264	(0.321)
OENEG	-0.456**	(0.228)	-0.446**	(0.227)	.	.	.	.	.	.
FU/TL	-0.726***	(0.235)	-0.740***	(0.235)	.	.	.	.	.	.
INTWO	-0.049	(0.135)	-0.036	(0.136)	.	.	.	.	.	.
CHIN	0.188**	(0.086)	0.198**	(0.086)	.	.	.	.	.	.
Patent	-0.119	(0.131)	-0.054	(0.132)	0.146	(0.135)	0.185	(0.136)	0.043	(0.137)
D2	.	.	0.584	(0.408)	.	.	0.705*	(0.422)	0.608	(0.419)
D3	.	.	0.602	(0.415)	.	.	0.588	(0.430)	0.508	(0.426)
D4	.	.	0.114	(0.407)	.	.	0.320	(0.417)	0.251	(0.414)
D5	.	.	0.571	(0.629)	.	.	0.205	(0.702)	0.286	(0.685)
D6	.	.	0.258	(0.460)	.	.	0.370	(0.459)	0.327	(0.458)
D7	.	.	0.325	(0.413)	.	.	0.456	(0.421)	0.463	(0.418)
D8	.	.	-0.087	(0.420)	.	.	0.167	(0.433)	0.061	(0.430)
D9	.	.	0.763	(1.036)	.	.	0.762	(1.086)	0.598	(1.052)
Exc Return	.	.	.	.	0.023	(0.023)	0.021	(0.023)	0.026	(0.021)
Stock Vol	.	.	.	.	0.164**	(0.073)	0.154**	(0.073)	0.118	(0.075)
No. observations	66,976		66,976		60,602		60,602		60,602	
No. fail	402		402		375		375		375	
No. firms	4965		4965		4558		4558		4558	
Wald test	119.9		157.0		36.26		53.17		114.0	
Pseudo-R^2	0.169		0.207		0.0453		0.0667		0.167	
LogL	-3095		-3083		-2887		-2881		-2852	

Small firms are the firms with total assets in the first quartile of the distribution. All coefficients are estimated for the Cox proportional hazard model with time varying covariates. The dependent variable in all models is bankruptcy dummy, that is 1 if a firm files for bankruptcy under Chapter 7 or 11 within 5 years and 0 otherwise. The pseudo R^2 is a measure of goodness of fit comparing the log-likelihood of the estimated model with the log-likelihood of a constant-only model. The Wald test analyses the overall significance of the estimated coefficients. SE represents robust standard errors which accounts for the possible presence of heteroscedasticity. ***, ** and * indicate 1%, 5%, 10% significance levels, respectively.

Table 3.10: Bankruptcy hazard model coefficients for US medium firms.

	1		2		3		4		5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-1.734***	(0.363)	-1.653***	(0.377)	-3.458***	(0.312)	-3.362***	(0.328)	-3.231***	(0.327)
TD/TA	1.830***	(0.198)	1.770***	(0.200)	1.138***	(0.126)	1.083***	(0.126)	0.943***	(0.151)
CL/CA	-0.077	(0.116)	-0.111	(0.115)	.	.	.	.	.	.
WC/TA	-0.737***	(0.271)	-0.806***	(0.274)	.	.	.	.	.	.
Log TA	0.072**	(0.036)	0.036	(0.036)	.	.	.	.	-0.085**	(0.039)
CASH/TA	.	.	.	.	-1.251***	(0.303)	-1.177***	(0.321)	-0.934***	(0.341)
OENEG	-0.790***	(0.166)	-0.789***	(0.169)	.	.	.	.	.	.
FU/TL	-2.026***	(0.189)	-2.002***	(0.189)	.	.	.	.	.	.
INTWO	-0.134	(0.122)	-0.090	(0.122)	.	.	.	.	.	.
CHIN	0.190***	(0.057)	0.190***	(0.057)	.	.	.	.	.	.
Patent	-0.281***	(0.096)	-0.195**	(0.097)	-0.262**	(0.103)	-0.174*	(0.105)	-0.139	(0.106)
D2	.	.	0.209	(0.203)	.	.	0.279	(0.224)	0.245	(0.226)
D3	.	.	0.203	(0.202)	.	.	0.260	(0.218)	0.257	(0.221)
D4	.	.	-0.442**	(0.206)	.	.	-0.359	(0.224)	-0.393*	(0.226)
D5	.	.	0.297	(0.575)	.	.	0.455	(0.608)	0.390	(0.605)
D6	.	.	-0.165	(0.242)	.	.	-0.059	(0.258)	-0.154	(0.259)
D7	.	.	-0.156	(0.207)	.	.	-0.227	(0.225)	-0.235	(0.228)
D8	.	.	-0.548**	(0.227)	.	.	-0.398	(0.244)	-0.437*	(0.246)
D9	.	.	-1.811**	(0.740)	.	.	-2.522**	(1.026)	-2.572**	(1.027)
Exc Return	.	.	.	.	0.059*	(0.035)	0.055*	(0.032)	0.052	(0.033)
Stock Vol	.	.	.	.	0.032	(0.033)	0.019	(0.032)	0.040	(0.032)
No. observations	135,134		135,134		130,751		130,751		130,751	
No fail	769		769		670		670		670	
No firms	7158		7158		6905		6905		6905	
Wald test	464.4		552.1		407.9		466.2		468.9	
Pseudo-R^2	0.280		0.338		0.198		0.260		0.270	
LogL	-6274		-6237		-5448		-5414		-5408	

Medium firms are the firms with total assets in the second and the third quartiles of the distribution. All coefficients are estimated for the Cox proportional hazard model with time varying covariates. The dependent variable in all models is bankruptcy dummy, that is 1 if a firm files for bankruptcy under Chapter 7 or 11 within 5 years and 0 otherwise. The pseudo R^2 is a measure of goodness of fit comparing the log-likelihood of the estimated model with the log-likelihood of a constant-only model. The Wald test analyses the overall significance of the estimated coefficients. SE represents robust standard errors which accounts for the possible presence of heteroscedasticity. ***, ** and * indicate 1%, 5%, 10% significance levels, respectively.

Table 3.11: Bankruptcy hazard model coefficients for US large firms.

	1		2		3		4		5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-5.744***	(0.745)	-5.659***	(0.777)	-6.154***	(0.786)	-6.233***	(0.809)	-6.124***	(0.807)
TD/TA	2.713***	(0.363)	2.600***	(0.344)	2.342***	(0.264)	2.203***	(0.254)	2.356***	(0.261)
CL/CA	-0.455*	(0.258)	-0.456*	(0.254)	.	.	.	.	.	.
WC/TA	-0.226	(0.547)	-0.449	(0.558)	.	.	.	.	.	.
Log TA	-0.315***	(0.088)	-0.312***	(0.086)	.	.	.	.	-0.270***	(0.091)
CASH/TA	.	.	.	.	1.789***	(0.570)	1.589***	(0.594)	0.804	(0.669)
OENEG	-0.514*	(0.296)	-0.496*	(0.284)	.	.	.	.	.	.
FU/TL	-3.610***	(0.497)	-3.054***	(0.521)	.	.	.	.	.	.
INTWO	0.480**	(0.244)	0.364	(0.252)	.	.	.	.	.	.
CHIN	-0.023	(0.113)	-0.044	(0.112)	.	.	.	.	.	.
Patent	-0.431***	(0.163)	-0.346**	(0.165)	-0.482***	(0.177)	-0.453**	(0.179)	-0.463**	(0.182)
D2	.	.	-0.003	(0.236)	.	.	-0.280	(0.237)	-0.231	(0.239)
D3	.	.	0.076	(0.229)	.	.	-0.066	(0.223)	-0.101	(0.224)
D4	.	.	-0.868***	(0.261)	.	.	-1.239***	(0.280)	-1.246***	(0.281)
D5	.	.	-43.702	(0.000)	.	.	-29.446***	(0.496)	-36.282***	(0.522)
D6	.	.	-0.840**	(0.337)	.	.	-1.134***	(0.342)	-1.059***	(0.344)
D7	.	.	-0.532**	(0.251)	.	.	-0.623**	(0.253)	-0.667***	(0.253)
D8	.	.	-0.838**	(0.379)	.	.	-1.099***	(0.400)	-1.118***	(0.399)
D9	.	.	-1.289***	(0.488)	.	.	-2.267***	(0.614)	-2.064***	(0.621)
Exc Return	.	.	.	.	-0.638	(0.453)	-0.543	(0.416)	-0.532	(0.405)
Stock Vol	.	.	.	.	-0.020	(0.043)	-0.029	(0.043)	-0.017	(0.043)
No observations	68,270		68,270		65,762		65,762		65,762	
No fail	268		268		232		232		232	
No firms	2919		2919		2827		2827		2827	
Wald test	300.6		362.8		268.9		4284		5791	
Pseudo-R^2	0.0471		0.0581		0.0383		0.0568		0.0599	
LogL	-1951		-1928		-1693		-1661		-1655	

Large firms are the firms with total assets in the fourth quartile of the distribution. All coefficients are estimated for the Cox proportional hazard model with time varying covariates. The dependent variable in all models is bankruptcy dummy, that is 1 if a firm files for bankruptcy under Chapter 7 or 11 within 5 years and 0 otherwise. The pseudo R^2 is a measure of goodness of fit comparing the log-likelihood of the estimated model with the log-likelihood of a constant-only model. The Wald test analyses the overall significance of the estimated coefficients. SE represents robust standard errors which accounts for the possible presence of heteroscedasticity. ***, ** and * indicate 1%, 5%, 10% significance levels, respectively.

3.5.3 Frailty Analysis

In order to take into consideration the possible heterogeneity arising from the common characteristics related to the same sectors, the Cox proportional hazard regressions are estimated using shared frailty models (equation 3.4.11). As discussed before, in a shared frailty model, frailties are shared across groups of firms operating in the same sector. In fact, using this model allows us to investigate whether default probabilities of firms in the same sector are correlated.

The shared frailties within each group are assumed to follow a gamma distribution in this study (equation 3.4.12). The frailty variance (θ), in the equation 3.4.12, which is estimated from the data, measures the variability of the frailty across groups. The log-likelihood ratio (LR) test, reported in Table 3.12, tests the null hypotheses that there are no sector specific factors or shared frailties ($H_0 : \theta = 0$) affecting the survival likelihood of firms.

In this regards, three models 1, 3 and model 5 excluding sector dummies, from the initially introduced models in Table 3.7, are estimated taking into account the shared frailties related to the sectors. The results of this analysis are reported in Table 3.12.

It can be noticed from the regression results for all models that the LR test supports the existence of the individual sector frailty effect across the sectors at 1% significance level, i.e. the nul hypothesis that $\theta = 0$ is confidently rejected. It can also be seen that the impact of the accounting and market ratios and their significance remain unchanged compared to the intial analysis of the bankruptcy. Also, the patent dummy remains significant at a 5% and 10% level and enters with a negative sign in all models. This analysis can also be considered as an additional robustness check for the previously observed impact of patent application on PD taking into account common characteristics of the same sector.

3.6 Conclusion

This chapter investigates the relationship between technology competition and corporate credit risk.

Table 3.12: Gamma Shared Frailty estimation results for US firms.

	1(model 1 earlier)		2(model 3 earlier)		3(model 5 earlier)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.111	(0.339)	-0.905***	(0.287)	-1.135***	(0.325)
TD/TA	1.918***	(0.173)	0.601***	(0.113)	0.815***	(0.140)
CL/CA	-0.307***	(0.105)	.	.	.	.
WC/TA	-0.298	(0.242)	.	.	.	.
Log TA	0.017	(0.018)	.	.	0.007	(0.020)
OENEG	-0.839***	(0.148)	.	.	.	.
FU/TL	-1.699***	(0.183)	.	.	.	.
INTWO	-0.138	(0.114)	.	.	.	.
CHIN	0.146***	(0.051)	.	.	.	.
Patent	-0.165**	(0.083)	-0.152*	(0.089)	-0.176*	(0.090)
CASH/TA	.	.	-0.442*	(0.252)	-0.661**	(0.274)
Exc Return	.	.	0.028	(0.028)	0.030	(0.028)
Stock Vol	.	.	-0.041	(0.029)	-0.045	(0.032)
No. observations	269,868		256,644		256,644	
No. sectors	10		10		10	
No. fail	1043		913		913	
No. firms	10468		10216		10216	
LR test ($\theta = 0$))	101.4***		78.08***		73.29***	
theta (θ)	0.175		0.242		0.230	
Wald test	261.7		106.7		113.5	
LogL	-8974		-7860		-7857	

All models are estimated by the Cox proportional hazard model with time varying covariates. The dependent variable in all models is bankruptcy dummy, that equals 1 if a firm files for bankruptcy chapter 7 or 11 within 5 years and 0 otherwise. The pseudo R^2 analyses the goodness of fit by comparing the log-likelihood of the estimated model with the log-likelihood of a constant-only model. The Wald test analyses the overall significance of the estimated coefficients. The likelihood ratio (LR) tests the null hypotheses that there are sector specific factors or shared frailties ($H_0 : \theta = 0$) affecting the survival likelihood of firms. "SE" column represents robust standard errors. ***, ** and * indicate 1%, 5%, 10% significanc levels, respectively.

Analysis of the primary patent application data at firm level reveals empirical evidence to support the intuition found in the literature that in a high technological competition environment, firms which fall behind in technological developments are more likely to experience default. Furthermore, the ability of patenting information as a measure of technology based innovative activities to forecast bankruptcy is significant in the presence of the typical bankruptcy predictors, which is consistent with the previous studies.

The results of this study indirectly support the findings in the existing literature that a patent application as an indication of a realized technology can guarantee higher revenue as well as benefiting the patenting firms through licensing income, enhancing competition and negotiation power. Such power is achieved by blocking competitors to have access to the new technology, gaining access to other new technologies by trading the patents with the competitors and also expanding marker power at international level.

This study, therefore, contributes both to the technology competition as well as to the corporate bankruptcy analysis literature. It has direct implications for the financial industry and indicates that lenders should use technology innovation indicators besides financial statements. Models that include non-financial information such as patenting activity, will help banks to gauge the level of risk that firms are exposed to more accurately, especially with regard to firms operating in technology driven industries. Measuring corporate default risk more accurately will be also helpful in reducing both asymmetric information and financial constraints faced by firms in the credit market.

Additionally, the importance of patenting for firms credit rating suggests more governmental and regulatory assistance, especially for small size firms. Such help, such as R&D investments and legal and financial support during the patenting process, will have a positive effect of reducing PD. Small and medium size firms, can be subject for further policy support in the area of technological innovation, since they make up a large share of firms in economies (Frietsch et al., 2013) and are an important source of innovation and employment growth in the economy,

The empirical findings of this research, suggest a crucial role of technological innovation evidenced by patent primary applications on improving financial performance and stability of companies.

Chapter 4

Firm Performance and Innovation in the US

4.1 Introduction

Innovation is the introduction of a new product, process or service that by applying different technology provides higher utility for the consumers than the existing products, process or service. Innovation is considered as an important contributor to economic growth and along with human capital is one of major sources of the wealth of the developed countries (Czarnitzki and Kraft, 2010). Enhancing technological capabilities also has a significant contribution in the economic performance of countries (Frietsch et al., 2014).

Although, majority of the investment in innovative activities is undertaken by governmental bodies such as research institutions and universities, a significant share can be attributed to private firms. However, firm's strategy to invest in innovative activities such as research and development (R&D) is to maximise their individual profitability not necessarily economic welfare (Czarnitzki and Kraft, 2010). There is a large strand of literature that studies various aspects of the impact of innovative activities on economic performance of firms which widely acknowledges the role of innovation and technological change as the main driver of firms economic growth, especially in the contemporary competitive environment.

Within this literature, a wide range of studies are conducted on the impact of R&D as an indicator of innovative activities of firms on the productivity and market valuation (Hall, 1993; Toivanen et al., 2002; Hsu et al., 2013; Sridhar et al., 2014) and financial stability (Franzen et al., 2007). Some features of R&D projects make their outcomes intrinsically uncertain. First, R&D is concerned with *priori* unknown outcomes that are associated with a high risk of failure. Second, even if the R&D projects are successful, there are long lags between the investment and introduction of the new product or process. This issue has been reflected less in the literature. Third, R&D has been traditionally subject to imitation and spill over effects to other firms, which clearly reduces profitability of successful projects. Therefore, despite the belief that R&D and innovative activities are beneficial for economy as a whole, it is not clear whether they are beneficial to any individual firms (Czarnitzki and Kraft, 2010).

As an alternative to R&D investments, many research studies use patenting activity indicators as a proxy of technological efficiency (Cincera, 1997). Eisdorfer and Hsu (2009) highlights several advantages for implementing patent data such as (i) compared to R&D expenditures and their associated uncertainty, patents are indication of competitive advantage and realized technologies exclusive to the business; (ii) the importance of patent filings has been appreciated by many firms due to the surge of patent competition and litigation in many industries; (iii) patents are a powerful tool in protecting higher income.

In the corporate finance literature patent activity has been identified as a significant covariate of various firm performance metrics such as market value (Blundell et al., 1999; Hall et al., 2005; Chen and Chang, 2010), productivity (Bloom and Reenen, 2002; Cainelli et al., 2006), access to capital (Mann and Sager, 2007) and firm growth (Deng et al., 1999; Andries and Faems, 2013). Patent indicators analysed in these studies are mainly the number of granted patents and patent citations, the patent family and overall number of patent applications. However, there has been a lack of comprehensive studies examining the impact of patent applications as an early sign of innovative activity on different aspects of firm performance. Focusing on patent applications instead of granted patent information in firm performance analysis has the important advantage of allowing an analysis of timely data, considering that three years typically elapse between filing and granting of a patent. According to the prevailing laws, an application is made public only eighteen months after filing Ernst (2001). This determines the minimum time lag between the innovation and issue of a patent. Moreover, innovations often result in patent applications that are subsequently rejected by patent offices and fail to be patented due to failure of meeting the requirements set by patent law (Ernst, 1995).

In this study we provide a new and detailed analysis of economic performance of patenting versus non-patenting US firms. Overall, this analysis indicates a higher capitalisation, increased liquidity and a lower leverage for patenting firms. Given these evidences, an interesting question to answer is whether these differences reflect actual changes following patenting or they are simply due to self-selection of larger, more profitable and productive firms opting for patenting for various reasons.

This study extends previous research by addressing this question and explores the link between patent application and firms' economic performance. Using a longitudinal data for US publicly listed firms between 1986 to 2011, we test the hypothesis that individual patent application leads to improvements in firm's financial performance. This hypothesis is tested for different aspects of firm performance including profitability, leverage, liquidity, size, credit rating quality and stock price. In contrast to the studies which considered the overall number of granted patents as a proxy for innovation, we study the effect of individual applications. This has an advantage of avoiding counting the so called strategic patenting on a mass scale as innovation.

While, the economic performance of firms three years before filing a patent is controlled, the impact of patent applications is tested on the difference between the after-patenting performance and past performance.

This chapter is structured as follows. Section 4.2 provides a summary of the existing literature of the connection between innovation and firm performance. Section 4.3 describes the data sources, data preparation techniques and the variables used in the analysis. The empirical strategy is explained in Section 4.6. Section 4.7 presents the empirical results and their interpretation. Finally Section 4.8 draws conclusion.

4.2 Motivation and Literature Review

4.2.1 Innovation and Economic Performance

The key role of innovation in explaining the performance of firms, industries and economic growth has been confirmed since the origin of economic thought (Cainelli et al., 2006). The early concept of innovation in economic development and entrepreneurship was introduced by Joseph Schumpeter, a German economist, in the Theory of Economic Development (Schumpeter, 1934). Schumpeter's theory centers around entrepreneurial innovations and their economic dimension as the key driver of economic growth. It can be argued that innovation is an essential for economic development of a country and competitiveness of an industry Beaver

(2002) .

In Schumpeter's theory, innovation, entrepreneurial activities and market power are defined as three essential elements for economic change. According to Schumpeter, innovation consists of creativity, research and development (R&D), new processes, new products or services and advances in technology (Lumpkin and Dess, 2001). Innovation as a process of idea creation and development of an invention leads to the introduction of a new product, process or service to the market (Aboulnasr et al., 2008).

In Schumpeter's view technological innovation leads to temporary monopolies with abnormal profits which would soon be competed away by imitators and rivals. He states that these transitory monopolies provide the incentive for firms to pay attention to innovation and develop new products and processes. Kim and Huarng (2011) also states that innovations can be accomplished through development of fresh knowledge or new products in the market that upturns a firm's leverage through increased profits and consumer satisfaction. As customer preferences change over the time, continuous assessment of market demands through constant innovations is required to maintain competitiveness in the market.

The importance of innovation as one of the prominent factors leading to a competitive advantage and superior profitability has been acknowledged by many authors (see for instance Roberts and Amit, 2003; Sandvik and Sandvik, 2003; Baker and Ahmad, 2010). The literature also confirms the positive relationship between innovation and general firm performance (Capon et al., 1990; Zahra and Das, 1993; Calantone et al., 1995; Han et al., 1998).

The existing literature stresses more about the positive impact of product, process and market innovation on firm performance (Bayus et al., 2003; Espallardo and Ballester, 2009; Alegre et al., 2006; Varis and Littunen, 2010). Improvement in the product quality through innovation could enhance firm performance and ultimately contribute to firm's competitive strengths (Garvin, 1987; Forker et al., 1996; Camison and Lopez, 2010). In other words, innovative firms, especially those operating in high technology industries, are very likely to become market leaders if they are able to develop the most recent updated and well-adopted technologies; however they are also exposed to high operational risk.

4.2.2 Firm Performance Indicators

Firm performance in general reflects outcomes achieved in delivering internal and external objectives of a firm (Lin et al., 2008). Performance is also termed growth (Dobbs and Hamilton, 2006; Wolff and Pett, 2006), survival, success and competitiveness (Rosli and Sidek, 2013). Firm's growth in the neo-classical economic theory is identified as a process of profit optimization that minimises the average cost of production (Trau, 1996). Additionally, Wernerfelt (1984), Peteraf (1993) and Mahoney (1995) related the business performance to the capabilities and resources that a business has as a source of sustainable competitive strengths in the market.

Depending on the organizational goals and strategies, firms apply different methods and indicators to measure their performance. These performance indicators are based on both financial and non-financial factors. However, most firms tend to prefer financial information to assess their performance (Grant et al., 1988). The most used financial information to measure performance is average annual occupancy rate, net profit after tax and return on investment (ROI) (Tavitiyaman et al., 2012) and return on assets (ROA) (Zahra, 2008). Other commonly applied accounting measures are profitability, productivity and growth (Garrigos-Simon and Marques, 2004; Garrigos-Simon et al., 2005; Bagorogoza and Waal, 2010).

However, business performance can not be judged solely by financial metrics. The leading indicators such as market position, customer satisfaction and innovation also often reflect company's economic performance, growth prospects and survival chances better than its reported earnings and other financial indicators (Becchetti and Sierra, 2003; Grunert et al., 2005). Krager and Parnell (1996) also argue that financial and non-financial information need to be combined in order to reflect the developments in internal and external environments.

It is the introduction of innovation that allows firms to prevail the pre-existing market conditions and to expand, build up monopolistic power and to enlarge their market share at the expense of non-innovating firms (Cainelli et al., 2006; Qui and Wan, 2015).

A typical proxy of innovation for studying its effect on firms' performance is patent stocks or the number of patents. However patent information is difficult to assess without detailed knowledge about the innovation. Complexity of the patent information is firstly related to high uncertainty and also high skewness of returns on R&D investments (Carpenter and Petersen, 2002). Secondly, the increase in strategic patenting makes the bulk use of patent data for valuation purposes problematic. Firms which are strategically patenting can have very few valuable patents because they do not patent to protect products against imitation, but rather to offset competitive powers. Consequently, with an established trend in strategic patenting, we can expect an increasing number of low value patents. Hence, it has become complicated for outsiders to evaluate and differentiate valuable patents from the low value ones (Blind et al., 2006, 2009). Thirdly, patent systems and laws can significantly affect the patenting process and the possibility of obtaining a patent.

(Griliches, 1990; Smith, 2005) list several shortcomings for the use of patent data as a proxy of inventive output. On the one hand, not all inventions are patented, and on the other, not all patented inventions represent true innovations. Moreover, other ways to protect inventions different from patenting can be preferred by firms, for example protection offered by secrecy instead of a patent right. Differences in patenting fees and rules also affect the propensity to patent innovations in different countries. The same point can be made with respect to some technologies and differences in patenting policies among countries. For example, whereas software patenting is possible in the US, it is limited in Europe. This considerably weakens the usefulness of patent data in a cross-industry comparisons. Another major problem of using the information related to patents is represented by the economic value of patents or, even more so, lack thereof (Arora et al., 2004; Lichtenthaler, 2009). This is related to the deflation of patent value that is driven by an increasingly large number of patent applications that are being filed around the world. This problem is amplified as strategic or defensive patenting is widely applied by companies to slow down competition in a specific market or to accumulate a patent portfolio to be used as bargaining power. For example, for each meaningful patented innovation, there might be a number of satellite patents extending the scope of protection.

With respect to a firm strategic behaviour, patents are often used by companies for, among others, such purposes as: to disclose information about innovations which might have been otherwise kept secret and to signal the availability of important technology available to a firm; or to prevent others from acquiring rights to a certain technology (Guellec and de la Potterie, 2001). This kind of behaviour resulted in “patent inflation” or “global patent warming”. Consequently, the distribution of patent value is skewed to the left or, in other words, only a small number of patents determine the value of patent portfolios (Gambardella et al., 2008).

Despite the above discussed drawbacks, Eisdorfer and Hsu (2009) outlines four advantages for applying patent information. First, unlike R&D expenditures which involve uncertainty, patents are indication of realized technologies of business value. Second, patents are a measure of competitive advantage because they are exclusive to the business. Third, the necessity of patent filings has been realized by many firms due to the surge of patent competition and litigation in many industries. Fourth, patents are a powerful tool in protecting higher income.

It can be assumed that inventions arising from R&D activity are likely to be protected from the possibility of exploitation by third parties by patenting them. This makes patents a robust measure of the output of inventive processes. Czarnitzki and Kraft (2010) studied the impact of innovation on firms’ profits by applying innovation measured as the patent stock being the depreciated sum of all past patent applications at the individual firm level. Lerner (1994) used “the number of subclasses into which the US Patent Office (USPTO) assigns the patent” as a proxy for patent scope to study its effect on firm value. Other patent indicators such as the number of patents granted (Scherer, 1965), patent citations and patent citations per patent granted (Narin et al., 1987), number of patent applications, share of patents granted, share of valid patents, share of foreign patent applications and patent value (Pederzoli et al., 2013) have been used to assess the impact of innovation on firms’ performance.

Despite a wide range of available metrics, little attention has been paid to analysing the impact of patent application on firm performance. Patent applications compared to other innovation indicators such as granted patents can be seen as early indicators since it can potentially take up to three years for a patent to be granted (Ernst, 2001). A patent application reserves the right for applicant against any other application on the same content throughout the assessment process. Meanwhile the applicant has the option to start utilizing the invention and negotiating for financing based upon the pending application. This can have a positive impact on firm's reputation and hence on its stock price. It can also boosts firm's profitability should the firm decide to implement the invention in its production, processes or services depending on the type of the innovation. This would be an advantage for the firm, especially in a highly competitive market. Patent application as an indicator of innovative capability of a firm is expected to positively affect the firm's financial position and its likelihood of survival in the long term. Thus, firms with poor or no innovative capability are expected to be more financially constrained, especially in technology driven industries.

4.2.3 Contribution

While, the existing literature on patenting and firm performance provide a good insight into the differences between patenting and non-patenting firms, they do not provide a meaningful conclusion of whether any part of these differences is due to applying for patents. In other words, it is possible that patenting firms are more efficient, productive or bigger even before patenting in which case patenting would be simply an indicator of the initial differences. It also could be the case that patenting firms were similar to the non-patenting firms before they start patenting and became more efficient, productive or bigger afterwards. This study focuses on analysing these differences and aims to examine whether changing from non-patenting to patenting status when a firm files its first and subsequent applications on the record is associated with significant changes in the firm's performance and stability. We provide a comprehensive analysis of the impact of individual patent applications on different aspects of firm performance including profitability, leverage, liquidity, activity, size, credit quality and stock performance. To the best of our knowledge, this is the first comprehensive empirical study of this kind in the patent and firm performance literature.

4.3 Data Description

4.3.1 Accounting Data

The data used in this study represents (i) accounting performance, (ii) stock returns, (iii) all patent applications that have been filed by a company worldwide and (iv) all distress and default events. These four types of data have been merged and augmented with credit scores prior to their use in our analysis.

We perform our analysis and test hypotheses for US listed companies with data covering period 1980–2011. Accounting data are collected as they are reported by Bloomberg and aggregated by the Risk Management Institute of the National University of Singapore (RMI NUS). Altogether we analysed quarterly accounts of more than 15,000 companies from various sectors along with industry classification codes. As it is common in the literature we exclude financial companies, asset backed securities, funds and government owned enterprises since the nature of these businesses is different from privately listed manufacturing firms, retailers, service providers, etc.

All accounting information is converted into financial ratios, the main purpose of which is to enable comparability across firms of different sizes and to avoid heteroscedasticity in the data. The ratios are grouped into five categories: profitability, leverage, liquidity, activity and size characterising company performance from different sides. In addition, industry sector are encoded with dummy variables.

4.3.2 Credit Default Data

In order to identify the status of a firm we consider credit default events: liquidation under Chapter 7 of the US Bankruptcy Code, restructuring under Chapter 11 of the US Bankruptcy Code and default on coupon or principle payments and covenant. For our analysis we used the credit event database of the RMI NUS. Our sample covers US listed companies for the same period as the quarterly accounting data. From the whole sample 1,339 companies (11.8%) experienced a credit event default at least once. On average 70 companies (0.6%) report default annually.

4.3.3 Patent Application Data

As a proxy of innovation we use primary patent applications submitted to 90 patent offices worldwide, which provides us with the 98% coverage of all patent applications in the world, or around 60 million patent applications worldwide and 964,358 applications by the US companies. Access to global data allows us to track all patents of US companies, not just the ones filed in the US. 58,654 patent applications were filed by the US companies overseas. The data were collected by the European Patent Office (EPO) and subsequently further enriched and provided to us by the Institute of Prospective Technological Studies (IPTS) of the European Commission (EC).

The patent application data contain information about the filing organisations and their address, country where the application was filed, the month and year of filing. Although patent information is publicly available from patent offices, its efficient use in research is considerably limited. The reason for this is the format in which row data are typically stored. The information regarding the names and addresses of patent applicants, assignees and inventors is not standardised. This does not allow for a direct matching with other types of information about company activities and needs to be specifically addressed.

4.3.4 Stock Price Data

Our study is based on the analysis of US listed companies for which stock price data are available. We use daily close stock prices as they are reported by Bloomberg. The data were aggregated and provided to us by the RMI NUS. In our analysis the stock return variable (Exc Return) is calculated as the return over the average price one month before and after the date of the financial report. This return is then annualized and benchmarked against the market return.

4.4 Data Aggregation and Merging

To sum up, we use four different types of data, which gives an in-depth and multifaceted picture of company operation:

1. quarterly accounts
2. default events
3. stock price data
4. primary patent applications

Aggregation of these data for the purpose of our study was not a trivial task and we would like to describe it in more detail here.

4.4.1 Merging Company

Every company in the quarterly accounts, default event and stock price databases was identified with its unique ticker and ID number. This allowed merging all records related to the same company from these three databases. What concerns the patent application data, company identification was much more tricky since company names were not standardised and could appear differently across different patent offices and even when reported by the same patent office. For example, General Electric can appear as GE, Inc. , General Electric, Inc. , GE, etc. This made automatic identification of company names and merging of records unreliable, a problem acknowledged in patent literature (Neuhäusler et al., 2011).

As a result, manual identification of company names in the patent application data became necessary for the tickers that could not be found automatically. It was an exhaustive process due to sheer size of the patent application data, substantial differences in spelling and the fact that not all companies filed applications. It required several search iterations reflecting different possible naming schemes.

Financial reports in the database are released quarterly, semi-annually and annually and reporting dates for companies are different and spread throughout the year. In this study we use quarterly reports. We index each quarterly financial

Table 4.1: The distribution of the number of primary patent applications across US listed companies matching accounting data.

Number of Patent Applications	Number of Firms
1	780 (29.06%)
2	251 (9.35%)
3	205 (7.64%)
4	180 (6.71%)
5	150 (5.59%)
> 5	1,118 (41.65%)

report by a unique time stamp according to the year and month of the report in order to arrange the financial information on a regular monthly basis for all firms. Therefore, each quarterly report receives a time stamps unique to the month and year of the report. The resulting monthly indexing of accounting data enables matching the monthly frequency of patent submission and credit event data.

Upon aggregating data of four different types we obtained a comprehensive data set containing 250,500 quarterly accounts for 8,977 US listed companies. From there, 2,684 companies filed at least one patent. the distribution of the number of the primary applications is reported in Table 4.1.

4.5 Variable Description and Summary Statistics

This section sums up the information about the data derived from the four sources and merged for the analysis in this study. Most analysis are used in the form of ratios, such as NI/TA= Net Income / Total Assets.

In order to exclude the effects of a potential year to another, of potential macroeconomic fluctuations from one year to another, we demean all financial ratios by subtracting their average for the same year. For the purposes of simplicity we do not use any special notations denoting demeaning. Thus, for example, NI/TA will correspond to a demeaned ratio. Similarly, annual excess returns are estimated as annual returns demeaned with the annual S&P returns.

Company ratings are estimated using a separate model following the moody's specification, which are subsequently mapped into the 1 to 19 scale with 1 for the least stable companies (C) and 19 for the safest ones (Aaa) (see (see Appendix C). These resulting ratings are also demeaned with the average of rating for each year to control for the economic conditions.

For controlling the effects of financial crises on company performance we introduce three dummies Cr, CrB and crA. Cr equals to 1 during the crisis. CrB and CrA during a 3 year period proceeding and following a crisis respectively. For all other periods they equal to 0. A summary of variables is reported in Table 4.2.

A small fraction of accounts contains ratios atypical for an operating company, even in distress, i.e. outliers. To deal with this issue we winsorise or cap all all variables at 5% and 95% quantiles. The summary statistics for all variables including the 5% and 95% quantiles is respresented in Table 4.3 separately for the companies that submitted at least one patent application and those who did not.

As the table indicates, the performance of firms with patent application is generally better than those without patent application. The analysis of the summary statistics reveals that: (i) patenting firms have a higher profitability. For instance, the median of NI/TA for patenting firms is higher than the median of NI/TA for non-patenting firms. (ii) the leverage is lower for patenting firms which presumably reveals their lower credit risk hence higher rating. (iii) liquidity ratios are higher for patenting firms, for example for the median of CASH/TA is higher for patenting firms then the median of CASH/TA for non-patenting firms. (iv) larger firms in terms of their total assets seem more likely to submit a patent application. (v) interestingly, excess returns are also higher for the patenting firms than the excess returns for the non-patenting firms. (vi) the standard deviation of all predictors, except for CASH/TA and Rating, are larger for the non-patenting firms compared to the patenting ones.

Table 4.4 reports pairwise correlation of all variables which vary significantly but do not exceed in absolute magnitude 0.7 which is the correlation between the leverage (TD/TA) and the rating class. According to Kennedy (2008), the OLS estimators suffer from multicollinearity if the correlation is equal to or greater than 0.8. Despite the large variation among the correlations reported in Table 4.4, all coefficients are below 0.8 and multicollinearity is not an issue here.

Table 4.2: Variable description. All ratios are demeaned with respect to the average for the same year.

Variable	Description
	Profitability
NI/TA	Return on assets: net income / total assets
Δ NI/TA	Average NI/TA over 3 years after a patent application - NI/TA 3 years before the application
	Leverage
TD/TA	Bank debt ratio: total bank debt / total assets
Δ TD/TA	Average TD/TA over 3 years after a patent application - TD/TA 3 years before the application
	Liquidity
CASH/TA	Cash and cash equivalents / total assets
Δ CASH/TA	Average CASH/TA over 3 years after a patent application - CASH/TA 3 years before the application
	Size
Log TA	Company size: logarithm of total assets
Δ Log TA	Average Log TA over 3 years after a patent application - Log TA 3 years before the application
	Activity
INV/S	Inventory turnover: inventories / sales
Δ INV/S	Average INV/S over 3 years after a patent application - INV/S 3 years before the application
	Rating Quality*
Rating	Estimated rating classes mapped into Moody's rating classes (see Appendix C) represented on a scale from 1 for the worst (C) to 19 for the best (Aaa)
Δ Rating	Average Rating over 3 years after a patent application - Rating 3 years before the application
	Market**
Exc Return	Annualized Stock Return - Annualized S&P 500 Return
MS	Market Share; Sales to total Sales in the same industry
	Patent Dummy
Patent	1 if a firm has at least one patent application filed at the time or before date of financial information, otherwise 0
	Crisis Dummies***
Cr	1 during the financial crises, otherwise 0
CrB	1 during 3 years before the financial crises, otherwise 0
CrA	1 during 3 years after the financial crises, otherwise 0
	Industry Dummies
D1, D2, D3	Basic Materials, Communications, Consumer Cyclical
D4, D5, D6	Consumer Non-cyclical, Diversified, Energy
D7, D8, D9	Industrial, Technology, Utilities
	1 for the respective industry otherwise 0

* More details about PD estimation and rating classes are provided in Appendix C.

** Stock volatility was investigated as a potential explanatory variable in all our regressions specifications and was always found to be insignificant. For this reason we exclude it from the subsequent analysis.

*** Two most recent financial crises that affected US market are considered to define the crisis dummies. First, is the dotcom crisis that started late February, 2000 and ended beginning June, 2000. Second, is the recent financial crisis that started late July, 2007 with recovery starting late April, 2010 (Fry et al., 2010).

Table 4.3: Summary statistics for non-patenting firms and patenting firms. $q_{0.05}$ and $q_{0.95}$ are respectively 5% and 95% quantiles.

	Non-patenting firms							Patenting firms						
Variable	Min	$q_{0.05}$	Mean	Med	$q_{0.95}$	Max	SD	Min	$q_{0.05}$	Mean	Med	$q_{0.95}$	Max	SD
Profitability														
NI/TA	-32.438	-0.243	-0.038	0.006	0.048	1.493	0.268	-8.825	-0.180	-0.021	0.008	0.048	1.358	0.147
Leverage														
TD/TA	0.000	0.000	0.297	0.251	0.788	2.989	0.305	0.000	0.000	0.214	0.165	0.601	2.971	0.247
Liquidity														
CASH/TA	0.000	0.001	0.083	0.044	0.296	0.400	0.094	0.000	0.003	0.0105	0.068	0.324	0.400	0.102
Size														
Log TA	-5.521	1.188	4.854	4.827	8.713	13.086	2.307	-2.919	1.971	5.516	5.539	9.513	13.649	2.295
Activity														
INV/S	0.000	0.000	0.475	0.182	1.479	49.953	1.406	0.000	0.000	0.627	0.479	1.545	49.260	1.234
Credit Quality														
Rating	1.000	7.000	7.767	9.000	11.000	19.000	1.609	1.000	7.000	9.407	9.000	12.000	19.000	1.651
Market														
Exc Return	-1.119	-0.538	-0.082	-0.088	0.385	4.516	0.303	-0.530	-0.312	-0.068	-0.047	0.168	0.407	0.145
MS	0.000	0.000	0.000	0.000	0.000	0.036	0.000	0.000	0.000	0.000	0.000	0.000	0.027	0.000

Table 4.4: Pearson correlation coefficients between demeaned variables.

Variable	NI/TA	TD/TA	CASH/TA	INV/S	Log TA	Rating	MS	Exc Return
NI/TA	1							
TD/TA	-0.12	1						
CASH/TA	-0.09	-0.30	1					
INV/S	-0.11	0.003	-0.02	1				
Log TA	0.28	0.11	-0.26	-0.11	1			
Rating	0.18	-0.67	0.41	0.02	-0.09	1		
MS	0.01	0.06	-0.04	-0.01	0.14	-0.06	1	
Exc Return	0.11	0.04	-0.11	-0.08	-0.003	-0.06	-0.01	1

4.6 Methodology

The data design applied for our analysis follows basic outlines of an event study. The purpose of the study is to analyse how an innovation, which is proxied by a priority patent application submitted at time t affects company performance compared to the performance prior to the innovation. This approach is relatively unexplored in the literature which mostly focuses on the overall volume of innovation proxied by patent portfolio (for example Lerner, 1994; Ernst, 2001; Neuhäusler, 2012; Frietsch et al., 2014). In contrast, we explore the impact of individual innovation and show that their effect quickly disappears and becomes undiscernible after a company has accumulated several patent applications. This allows us to to answer a critical question, namely what is the value of a typical innovation leading to a patent application in terms of its impact on the company profitability, capital structure (leverage), liquidity, size, credit quality and stock performance.

For every priority patent application at time t we collect two types of information. Firstly, accounting and market performance characteristics such as profitability, leverage, liquidity, size, activity, credit quality, excess returns and market share over the 3 years (12 quarters) following the application. For these characteristics we estimate the average over the whole 3 year period in order to reduce the variability related to the fact that it can take different time for various types of innovation to affect the company performance. Secondly, the post-patent application performance is benchmarked against the performance of the company three years prior to the application. The three years period is deemed to be sufficiently long for measuring the reference performance not affected by innovation.

In order to exclude the effect of potential macroeconomic fluctuations from one year to another we demeaned all financial ratios and ratings from every year by subtracting their average for the same year. Annual excess returns are demeaned with respect to the annual S&P returns.

The control group are the companies without patent application in our data. In order to control for the differences in the distribution across years for innovating and non-innovating companies we randomly select for each year the same number of records for non-innovating companies as the number of patent applications made by innovating companies.

We focus our analysis on the estimation of the impact of the first primary patent applications. We have no evidence that companies had been applying for patent prior to them, so they are expected to have the maximum significance.

Our measure of change for every company performance characteristic is its difference between the post-patent application period and the latest available record at least three years prior to the application. For example, for NI/TA we will denote this difference as $\Delta\mathrm{NI/TA}_t$. The index t refers to the month of submitting the application. For non-innovating companies which do not apply for patent, it is a random date.

In order to quantify the effects of a patent application on company performance we apply the following regression specification.

$$\begin{aligned} \Delta(X_{it} - \overline{X_t}) = \beta_0 \quad &+ \quad \beta_1(X_{it} - \overline{X_t}) \\ &+ \quad \beta_2 Patent_{it} \\ &+ \quad \beta_3(MS_{it} - \overline{MS_t}) \\ &+ \quad \beta_4 Crisis_{it} + \beta_5 D_{it} + \epsilon_{it} \end{aligned} \tag{4.6.1}$$

Here, $X_{it} = (\mathrm{NI/TA}, \mathrm{TD/TA}, \mathrm{CASH/TA}, \mathrm{INV/S}, \mathrm{Log\ TA}, \mathrm{Rating}, \mathrm{Exc\ Return})_{it}$ is a vector of performance characteristics for company i registered at the end of the month t.

$Crisis_{it} = (\text{Cr, CrB, CrA})_{it}^{\top}$ is a vector of the crisis, pre-crisis and post-crisis dummies.

$D_{it} = (\text{D}_2, \text{D}_3, \ldots, \text{D}_9)_{it}^{\top}$ is a vector of industry dummies.

β_0, β_2 and β_3 are 7×1 dimensional vectors and β_1, β_4 and β_5 are 7×7, 7×3, and 7×8 dimensional matrices of coefficients, respectively, ϵ_{it} is a 7×1 dimensional vector of residuals.

4.7 Empirical Results

Following the model specification (Equation 4.6.1) and the data described in Section 4.5, this section provides empirical evidence of the impact of patent applications on firm performance.

Firstly, controlling for a wide range of financial measures, we analyse the effects of the first ever priority patent application registered for the company in our data on firm performance followed by the analysis of the subsequent priority applications, if they are available, filed by the same companies. This will allow us to isolate the effects of individual patents and focus on the patents that are associated with innovation in contrast to the portfolio of patents filed for strategic defensive purposes. We investigate a comprehensive set of performance measure: profitability, leverage, liquidity, credit quality, stock market performance and company size. Secondly, we check the robustness of our results by analysing the combined effects of the first on record patent applications on performance using several alternative specifications. Although the main purpose of this study is to uncover the relationship between innovation and company performance, we also can identify effects related to other performance drivers.

4.7.1 Profitability

Table 4.5 reports the effects of a priority patent application on profitability measured by Δ NI/TA following the specification in Section 4.6, controlled by the benchmark accounting and market performance, credit rating, crisis conditions and industry. It is evident that patent applications do not have a significant effect on profitability. This is also confirmed by the results reported in Table 4.11. Our result confirms previously reported results of no effect of patents on profitability (Comanor and Scherer, 1969; Ernst, 2001).

The traditional explanation offered in the literature attributes the no effect of patent on profitability (NI/TA) to the expanding R&D investment that increases operating costs and depresses operating income (Hsu et al., 2013). We find that an alternative explanation is more plausible. Innovation leading to a patent application might boost productivity and contribute to the increase of the net income. However, at the same time the value of innovation expressed as discounted value of future cash flows associated with it enhances the company valuation (see Tables 4.16 and 4.10). Both effects combine to leave the profitability (NI/TA) unchanged.

4.7.2 Leverage

We find a negative impact of priority patent applications on leverage (see Tables 4.6 and 4.12). The impact is large and in most cases statistically significant, specially for first priority application on record. The significance is declining from the first to the fifth patent application due to a smaller sample size. One priority application reduces the leverage by around 3%. This result consistent with the literature (Vincente-Lorente, 2001; O'Brien, 2003) confirms the view that corporate capital structure does not only depend on tax regulatory, product market and exogenous industry factors, but is also related to firm's technological strategy and competitive capabilities. The significant negative effect of an individual patent application, combined with the fact that innovation is conductive to company growth means that the capital increase is achieved more through the appreciation of own capital rather than through borrowing.

4.7.3 Liquidity

Tables 4.7 and 4.13 reveals a predominantly positive but sometimes insignificant effects of patent applications on liquidity. This result confirms, although not conclusively, the expectations that patents provide their owners with multiple channels of obtaining more cash flows. These channels are, for example, commercialisation of the technology introduced by the patent and licensing or selling that technology. Additionally effective liquidity management is essential to firm's success, especially in research intensive industries characterised by higher risks. Therefore, the level of firm's technology intensity proxied by patent application is positively related to the cash position of a firm.

The internal mechanism explaining higher liquidity after filing a patent application is likely to be the reduction of knowledge asymmetries associated with R&D. As soon as the patent application is submitted and after the period of 18 months the content of the patent is made public, the information about patent can be assessed by external capital providers and lead to the reduction of external financing costs and improvement of liquidity.

4.7.4 Credit Quality

The relationship between firm's credit quality on one side and its patenting activity on the other has been insufficiently investigated in the literature. As anticipated, our empirical results presented in Tables 4.8 and 4.14 suggest that patenting as an output of R&D and a signal to outsiders, reduces the likelihood of financial distress and the probability of bankruptcy. The literature confirms the relevance of patents for improving credit quality and associates with the patents a higher probability of positive returns in the future and views them as a competitive weapon to protect higher returns (Neuhäusler et al., 2011; Pederzoli et al., 2013). We identify an additional channel of improving credit ratings through the reduction of the need for external financing manifested in lower leverage and higher liquidity. We do not find a confirmation of the mechanism that patenting improves due to higher profitability, although profitability as well as leverage and liquidity are widely acknowledged determinants of the credit rating.

4.7.5 Stock Performance

A significant aspect of overall performance for listed companies in our sample is stock market performance. The results in Tables 4.9 and 4.15 confirm that applying for a patent boosts company market valuation. This conclusion is largely confirmed in the existing literature (Belenzon and Patacconi, 2013). Two mechanisms are cited to explain the positive effect of patent applications. Firstly, R&D, on which the application is based, provides a company with a competitive advantage over its peers in the industry, creates new sources of income and protects from competition. Secondly, it is argued that a patent application signals to the market the quality of invention and overall corporate technological strength. The stock market reacts by pricing in the expected discounted value of increased future cash flows and evaluates the benefits of the invention immediately (Pakes, 1985). An interesting contribution of this study is the observation that it is only the first primary patent application on record that has a significant impact.

4.7.6 Total Assets

The results reported in Tables 4.10 and 4.16 provide a strong confirmation that patenting activities are closely and positively associated with firm's growth. Firm's size is usually measured in terms of sales, capital, employment or value added. Our analysis utilising capital or total assets as a measure of firm's size contributes to the existing literature by examining the impact of patenting on firm size and presents a similar conclusion (Comanor and Scherer, 1969; Ernst, 2001). For example Ernst (2001) also confirms a positive correlation between a patent application and firm turnover, another measure of firm size, with a time lag of 2 to 3 years after the priority application.

Although the relationship between patenting activities and growth is strong, it is hard to distinguish which part of the growth can be directly attributed to an innovation culminating in a patent application and which to underlying transformational process of which innovation in only a part. In any case we have string evidence to confirm the hypothesis that innovation significantly contributes to firm growth, even when we could not find any evidence that it contributes to the profitability of its assets.

These results confirm effectiveness of patent application information in studying companies productivity and growth compared to other public information on firms' innovative efforts such as R&D. R&D expenditures as the only innovation related measure which appear periodically on firms' financial statements, provide no adequate and timely information about their nature, quality and potential associated benefits. Furthermore, investors can not distinguish from the R&D costs innovation competence amongst companies. It becomes even more difficult for investors to assess the innovation capabilities of small firms which generally do not classify some of their innovative activities as R&D investments (Deng et al., 1999).

Moreover, our analysis corresponds to the recent reforms in patenting system in terms of strengthening patent protection since 1980s. Some examples of such reforms are (i) creation of a specialised "pro-patent" Court of Appeal in the US in 1982 with the objective of providing consistency in patent litigations; (ii) adopting a set of harmonised standards of intellectual property protection via international agreements, (iii) broadening definition of patentable subject matters to biotechnology and software, all of which give firms strong incentive to apply for patent protection (Belenzon and Patacconi, 2013). These reforms could have most likely affected the monopoly and quality signaling power of patents, the impact of which has been confirmed by our empirical findings.

4.7.7 Results Overview

Overall, the results of this study confirms both direct and indirect benefits associated with innovation on corporate performance stated in corporate literature: (i) the direct benefits which mainly reflect the transitory effect of innovation on revenue and potentially profitability, (ii) the indirect benefits such as less sensitivity to adverse macroeconomic factors and more ability to take advantage of spillovers (Geroski et al., 1993). Furthermore, the empirical findings of this study is theoretically consistent with the Schumpeters view on competition, indicating that generating technological capabilities and knowledge via R&D is a key issue for future economic progress.

Table 4.5: Individual impact of the first five patent applications on profitability (Δ NI/TA)

	Patent 1		Patent 2		Patent 3		Patent 4		Patent 5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.740***	(0.008)	-0.816***	(0.008)	-0.859***	(0.009)	-0.870***	(0.010)	-0.872***	(0.009)
TD/TA	-0.004	(0.004)	-0.012***	(0.005)	-0.012**	(0.005)	-0.010	(0.006)	0.007	(0.005)
CASH/TA	-0.015*	(0.009)	-0.033***	(0.011)	-0.009	(0.012)	0.007	(0.013)	-0.037***	(0.012)
INV/S	-0.002**	(0.001)	-0.003***	(0.001)	0.002**	(0.001)	-0.003***	(0.001)	-0.013***	(0.001)
Log TA	0.008***	(0.000)	0.008***	(0.000)	0.009***	(0.001)	0.010***	(0.001)	0.008***	(0.001)
Patent	-0.001	(0.002)	-0.004	(0.003)	-0.007*	(0.004)	-0.007	(0.005)	-0.006	(0.006)
Rating	0.001	(0.001)	0.001*	(0.001)	0.000	(0.001)	0.000	(0.001)	0.003***	(0.001)
MS	-11.925***	(3.678)	-30.134***	(9.149)	-13.278**	(5.965)	-14.764***	(6.300)	-3.202	(3.735)
Exc Return	0.602***	(0.002)	0.072***	(0.003)	0.076***	(0.004)	0.067***	(0.004)	0.073***	(0.004)
CrD	0.016***	(0.002)	0.017***	(0.003)	0.014***	(0.003)	0.004	(0.003)	0.015***	(0.003)
CrB	0.011***	(0.002)	0.013***	(0.002)	0.014***	(0.002)	0.010***	(0.003)	0.014***	(0.003)
CrA	0.018***	(0.002)	0.023***	(0.003)	0.019*	(0.003)	0.019***	(0.003)	0.024***	(0.003)
D2	-0.022***	(0.004)	-0.020***	(0.005)	-0.019***	(0.006)	-0.018***	(0.006)	-0.030***	(0.006)
D3	0.007*	(0.004)	0.006	(0.005)	0.005	(0.005)	0.011*	(0.006)	0.001	(0.006)
D4	-0.003	(0.004)	-0.005	(0.004)	-0.003	(0.005)	-0.002	(0.006)	0.000	(0.006)
D5	0.030**	(0.014)	-0.021	(0.016)	0.009	(0.018)	0.002	(0.025)	0.053***	(0.017
D6	0.001	(0.004)	-0.008*	(0.005)	0.002*	(0.006)	0.004	(0.006)	-0.009	(0.006)
D7	0.005	(0.004)	0.001	(0.004)	0.008	(0.005)	0.010*	(0.006)	0.001	(0.006)
D8	-0.003	(0.004)	-0.003	(0.005)	-0.010*	(0.006)	-0.008	(0.006)	-0.007	(0.006)
D9	-0.010**	(0.005)	-0.008	(0.005)	-0.005	(0.006)	-0.002	(0.007)	-0.012*	(0.007)
R^2	0.272		0.355		0.452		0.327		0.395	
$Adj R^2$	0.271		0.354		0.451		0.326		0.395	
$F Statistics$	402.70***		474.03***		677.49***		373.72***		508.03***	

***, **, *: 1%, 5%, 10% significance.

Table 4.6: Individual impact of the first five patent applications on leverage (Δ TD/TA)

	Patent 1		Patent 2		Patent 3		Patent 4		Patent 5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.160 ***	(0.017)	-0.266 ***	(0.017)	-0.141 ***	(0.016)	0.024	(0.017)	-0.178 ***	(0.017)
TD/TA	-0.490 ***	(0.008)	-0.448 ***	(0.010)	-0.538 ***	(0.010)	-0.537 ***	(0.010)	-0.537 ***	(0.010)
CASH/TA	0.003	(0.018)	-0.104 ***	(0.022)	0.022	(0.022)	-0.040 *	(0.022)	0.014	(0.024)
INV/S	0.004 ***	(0.001)	0.000	(0.001)	-0.007 ***	(0.001)	0.006 ***	(0.002)	0.011 ***	(0.002)
Log TA	0.000	(0.001)	0.000	(0.001)	-0.001	(0.001)	0.000	(0.001)	-0.002	(0.001)
Patent	-0.027 ***	(0.003)	-0.030 ***	(0.005)	-0.024 ***	(0.007)	-0.018 **	(0.008)	-0.021 *	(0.012)
Rating	-0.013 ***	(0.001)	-0.009 ***	(0.002)	-0.012 ***	(0.001)	-0.014 ***	(0.002)	-0.022 ***	(0.002)
MS	-15.556 **	(7.611)	-22.127	(18.523)	-2.351	(11.210)	-4.792	(10.618)	13.368 *	(7.219)
Exc Return	-0.185 ***	(0.005)	-0.234 ***	(0.006)	-0.201 ***	(0.007)	-0.196 ***	(0.007)	-0.225 ***	(0.007)
CrD	-0.022 ***	(0.005)	-0.007	(0.006)	-0.002	(0.006)	-0.002	(0.006)	-0.001	(0.006)
CrB	-0.011 ***	(0.004)	-0.012 ***	(0.004)	-0.009 **	(0.005)	-0.006	(0.005)	-0.007	(0.005)
CrA	-0.018 ***	(0.005)	-0.005	(0.005)	0.014 **	(0.005)	-0.014 **	(0.006)	0.002	(0.006)
D2	0.023 ***	(0.008)	0.007	(0.010)	0.056 ***	(0.010)	0.048 ***	(0.010)	0.048 ***	(0.011)
D3	0.016 **	(0.008)	-0.025 ***	(0.009)	0.030 ***	(0.010)	0.046 ***	(0.010)	-0.007	(0.011)
D4	0.019 ***	(0.007)	-0.036 ***	(0.009)	0.035 ***	(0.010)	0.009	(0.009)	-0.014	(0.011)
D5	0.041	(0.030)	0.141 ***	(0.032)	0.109 ***	(0.034)	-0.003	(0.042)	-0.033	(0.033)
D6	0.035 ***	(0.008)	0.008	(0.010)	0.034 ***	(0.011)	0.037 ***	(0.011)	0.058 ***	(0.012)
D7	-0.001	(0.007)	-0.043 ***	(0.009)	0.015	(0.010)	0.017 *	(0.010)	-0.027 ***	(0.011)
D8	-0.037 ***	(0.008)	-0.080 ***	(0.010)	-0.035 ***	(0.011)	-0.018 *	(0.011)	-0.057 ***	(0.012)
D9	0.034 ***	(0.009)	-0.012	(0.011)	0.052 ***	(0.011)	0.035 ***	(0.011)	0.007	(0.013)
R^2	0.224		0.205		0.232		0.245		0.236	
$Adj R^2$	0.223		0.204		0.231		0.244		0.235	
$F Statistics$	310.780***		222.260***		247.710***		249.360***		241.260***	

***, **, *: 1%, 5%, 10% significance.

Table 4.7: Individual impact of the first five patent applications on liquidity (Δ CASH/TA)

	Patent 1		Patent 2		Patent 3		Patent 4		Patent 5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.027***	(0.006)	-0.039***	(0.005)	-0.010 **	(0.005)	-0.012 **	(0.006)	-0.006	(0.005)
TD/TA	-0.034***	(0.003)	-0.022***	(0.003)	-0.030 ***	(0.003)	-0.008 **	(0.003)	-0.025 ***	(0.003)
CASH/TA	-0.734 ***	(0.006)	0.257 ***	(0.007)	0.251 ***	(0.007)	0.248 ***	(0.007)	0.246 ***	(0.007)
INV/S	0.000	(0.000)	0.001 *	(0.000)	0.001 ***	(0.000)	0.001	(0.001)	0.000	(0.001)
Log TA	-0.003 ***	(0.000)	-0.003 ***	(0.000)	-0.003 ***	(0.000)	-0.003 ***	(0.000)	-0.005 ***	(0.000)
Patent	0.001	(0.001)	0.008 ***	(0.002)	0.009 ***	(0.002)	0.005 *	(0.003)	0.010 ***	(0.004)
Rating	0.003 ***	(0.000)	0.004 ***	(0.001)	0.002 ***	(0.000)	0.006 ***	(0.001)	0.003 ***	(0.001)
MS	-3.243	(2.547)	11.276 *	(5.942)	-3.147	(3.591)	-2.683	(3.503)	1.150	(2.222)
Exc Return	0.032 ***	(0.002)	0.029 ***	(0.002)	0.038 ***	(0.002)	0.035 ***	(0.002)	0.037 ***	(0.002)
CrD	-0.001	(0.002)	0.001	(0.002)	0.001	(0.002)	0.002	(0.002)	0.005 **	(0.002)
CrB	-0.003 **	(0.001)	0.000	(0.001)	0.001	(0.001)	0.000	(0.002)	0.002	(0.002)
CrA	-0.001	(0.002)	0.000	(0.002)	-0.004 **	(0.002)	-0.002	(0.002)	-0.003	(0.002)
D2	0.024 ***	(0.003)	0.018 ***	(0.003)	0.026 ***	(0.003)	0.015 ***	(0.003)	0.026 ***	(0.004)
D3	0.004	(0.003)	0.008 ***	(0.003)	0.003	(0.003)	-0.006 *	(0.003)	0.011 ***	(0.003)
D4	0.014 ***	(0.002)	0.016 ***	(0.003)	0.013 ***	(0.003)	0.008 **	(0.003)	0.017 ***	(0.003)
D5	0.031 ***	(0.010)	0.037 ***	(0.010)	0.034 ***	(0.011)	0.028 **	(0.014)	0.035 ***	(0.010)
D6	-0.008 ***	(0.003)	-0.004	(0.003)	-0.011 ***	(0.003)	-0.017 ***	(0.004)	-0.013 ***	(0.004)
D7	0.004	(0.002)	0.001	(0.003)	-0.002	(0.003)	-0.008 **	(0.003)	0.002	(0.003)
D8	0.047 ***	(0.003)	0.051 ***	(0.003)	0.049 ***	(0.003)	0.050 ***	(0.004)	0.051 ***	(0.004)
D9	-0.016 ***	(0.003)	-0.012 ***	(0.003)	-0.019 ***	(0.004)	-0.022 ***	(0.004)	-0.015 ***	(0.004)
R^2	0.410		0.237		0.228		0.236		0.225	
$Adj R^2$	0.409		0.236		0.227		0.235		0.224	
$F Statistics$	747.930***		266.780***		242.270***		237.140***		266.500***	

***, **, *: 1%, 5%, 10% significance.

Table 4.8: Individual impact of the first five patent applications on credit quality (Δ Rating)

	Patent 1		Patent 2		Patent 3		Patent 4		Patent 5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	0.889***	(0.094)	0.772***	(0.087)	0.893***	(0.084)	-0.184**	(0.088)	0.242***	(0.083)
TD/TA	-0.940***	(0.045)	-1.053***	(0.053)	-1.029***	(0.051)	-0.722***	(0.053)	-0.646***	(0.051)
CASH/TA	0.019	(0.100)	0.682***	(0.114)	0.444***	(0.012)	0.207*	(0.115)	-0.379***	(0.118)
INV/S	0.040***	(0.008)	0.026***	(0.006)	0.097***	(0.007)	0.017**	(0.008)	0.027***	(0.009)
Log TA	-0.005	(0.004)	0.009*	(0.005)	0.006	(0.005)	0.014***	(0.005)	0.001	(0.005)
Patent	0.156***	(0.018)	0.131***	(0.027)	0.151***	(0.035)	0.077*	(0.044)	0.072*	(0.059)
Rating	-0.664***	(0.007)	-0.689***	(0.008)	-0.744***	(0.008)	-0.682***	(0.009)	-0.601***	(0.009)
MS	-83.399**	(41.439)	-80.386***	(43.157)	-74.500	(57.636)	-91.428***	(40.055)	-96.270***	(35.427)
Exc Return	0.965***	(0.027)	1.196***	(0.033)	1.066***	(0.036)	1.052***	(0.034)	1.083***	(0.033)
CrD	0.179***	(0.027)	0.137***	(0.029)	0.048	(0.031)	0.033	(0.031)	0.087***	(0.031)
CrB	0.077***	(0.020)	0.093***	(0.023)	0.067***	(0.023)	0.030	(0.024)	0.070***	(0.025)
CrA	0.146***	(0.025)	0.081***	(0.027)	-0.032	(0.028)	0.047	(0.030)	0.040	(0.031)
D2	-0.254***	(0.044)	-0.319***	(0.050)	-0.339***	(0.054)	-0.358***	(0.054)	-0.257***	(0.056)
D3	-0.178***	(0.042)	-0.178***	(0.048)	-0.290***	(0.051)	-0.344***	(0.051)	-0.046	(0.054)
D4	-0.131***	(0.040)	-0.022	(0.046)	-0.225***	(0.050)	-0.179***	(0.050)	0.006	(0.052)
D5	-0.349**	(0.162)	-0.391**	(0.164)	-0.960***	(0.174)	-0.279	(0.222)	0.349**	(0.159)
D6	-0.368***	(0.046)	-0.442***	(0.052)	-0.512***	(0.056)	-0.500***	(0.057)	-0.514***	(0.059)
D7	-0.106***	(0.040)	-0.035	(0.046)	-0.165***	(0.050)	-0.196***	(0.051)	0.010	(0.053)
D8	-0.008	(0.045)	0.090*	(0.051)	-0.050	(0.055)	-0.016	(0.057)	0.0118**	(0.059)
D9	-0.533***	(0.005)	-0.436***	(0.055)	-0.657***	(0.059)	-0.613***	(0.059)	-0.385***	(0.062)
R^2	0.389		0.375		0.445		0.379		0.342	
$Adj R^2$	0.389		0.374		0.445		0.378		0.341	
$F Statistics$	686.44***		517.04***		658.69***		468.23***		404.17***	

***, **, *: 1%, 5%, 10% significance.

Table 4.9: Individual impact of the first five patent applications on stock performance (Exc Return)

	Patent 1		Patent 2		Patent 3		Patent 4		Patent 5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	0.256 ***	(0.022)	0.213 ***	(0.019)	0.256 ***	(0.017)	0.234 ***	(0.020)	0.259 ***	(0.019)
TD/TA	0.099 ***	(0.011)	0.055 ***	(0.012)	0.043 ***	(0.011)	0.042 ***	(0.012)	0.029 **	(0.012)
CASH/TA	-0.194 ***	(0.024)	-0.267 ***	(0.025)	-0.091 ***	(0.023)	-0.188 ***	(0.026)	-0.273 ***	(0.027)
INV/S	-0.008 ***	(0.002)	-0.002	(0.001)	0.002	(0.001)	-0.006 ***	(0.002)	-0.018 ***	(0.002)
Log TA	-0.008 ***	(0.001)	-0.009 ***	(0.001)	-0.011 ***	(0.001)	-0.010 ***	(0.001)	-0.010 ***	(0.001)
Patent	0.011 ***	(0.004)	-0.014	(0.009)	0.002	(0.011)	-0.003	(0.015)	0.008	(0.019)
Rating	-0.006 ***	(0.002)	-0.007 ***	(0.002)	-0.009 ***	(0.002)	-0.002	(0.002)	-0.004 **	(0.002)
MS	0.061 ***	(0.002)	0.068 ***	(0.003)	0.072 ***	(0.004)	0.065 ***	(0.004)	0.070 ***	(0.003)
Exc Return	26.348 ***	(9.864)	68.838 ***	(21.113)	20.974 *	(12.021)	63.510 ***	(12.515)	-3.017	(8.143)
CrD	-0.013 ***	(0.006)	-0.065 ***	(0.007)	-0.033 ***	(0.007)	-0.031 ***	(0.007)	-0.023 ***	(0.007)
CrB	-0.041 ***	(0.005)	-0.050 ***	(0.006)	-0.043 ***	(0.005)	-0.036 ***	(0.006)	-0.047 ***	(0.006)
CrA	-0.095 ***	(0.006)	-0.134 ***	(0.006)	-0.138 ***	(0.006)	-0.114 ***	(0.007)	-0.144 ***	(0.007)
D2	0.057 ***	(0.011)	0.029 ***	(0.011)	-0.005	(0.011)	-0.027 **	(0.012)	0.040 ***	(0.013)
D3	0.037 ***	(0.010)	0.020 *	(0.010)	-0.009	(0.011)	0.004	(0.012)	0.050 ***	(0.013)
D4	0.077 ***	(0.010)	0.065 ***	(0.010)	0.019 *	(0.010)	0.015	(0.011)	0.052 ***	(0.012)
D5	-0.144 ***	(0.039)	-0.024	(0.036)	-0.149 ***	(0.036)	-0.341 ***	(0.050)	0.078 **	(0.037)
D6	0.111 ***	(0.011)	0.099 ***	(0.012)	0.111 ***	(0.012)	0.055 ***	(0.013)	0.123 ***	(0.013)
D7	0.049 ***	(0.010)	0.057 ***	(0.010)	0.006	(0.010)	0.020 *	(0.011)	0.058 ***	(0.012)
D8	0.041 ***	(0.011)	0.028 **	(0.011)	0.000	(0.012)	-0.054 ***	(0.013)	0.026 *	(0.013)
D9	0.039 ***	(0.012)	0.029 **	(0.012)	0.017	(0.012)	-0.027 **	(0.013)	0.034 **	(0.014)
R^2	0.048		0.061		0.071		0.056		0.069	
$Adj R^2$	0.047		0.060		0.070		0.054		0.068	
$F Statistics$	57.80***		51.36***		57.69***		41.53***		52.79***	

***, **, *: 1%, 5%, 10% significance.

Table 4.10: Individual impact of the first five patent applications on firm size (Δ Log TA)

	Patent 1		Patent 2		Patent 3		Patent 4		Patent 5	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.071	(0.067)	-0.354 ***	(0.061)	0.318 ***	(0.057)	-0.226 ***	(0.061)	-0.067	(0.058)
TD/TA	-0.042	(0.032)	-0.140 ***	(0.037)	-0.093 ***	(0.035)	-0.010	(0.036)	-0.119 ***	(0.035)
CASH/TA	0.687 ***	(0.071)	1.032 ***	(0.080)	1.077 ***	(0.077)	1.092 ***	(0.079)	1.166 ***	(0.083)
INV/S	-0.046 ***	(0.006)	-0.032 ***	(0.004)	-0.009 *	(0.005)	-0.033 ***	(0.006)	-0.040 ***	(0.006)
Log TA	-0.062 ***	(0.003)	-0.045 ***	(0.004)	-0.060 ***	(0.003)	-0.054 ***	(0.003)	-0.045 ***	(0.004)
Patent	0.219 ***	(0.013)	0.222 ***	(0.019)	0.220 ***	(0.024)	0.337 ***	(0.030)	0.257 ***	(0.041)
Rating	-0.003	(0.005)	-0.030 ***	(0.006)	-0.002	(0.005)	0.000	(0.006)	-0.016 **	(0.006)
MS	28.577	(29.473)	-88.790	(67.648)	5.230	(39.305)	12.704	(38.348)	-30.490	(24.767)
Exc Return	0.584 ***	(0.019)	0.740 ***	(0.023)	0.733 ***	(0.024)	0.642 ***	(0.024)	0.612 ***	(0.023)
CrD	-0.248 ***	(0.019)	-0.258 ***	(0.020)	-0.238 ***	(0.021)	-0.233 ***	(0.021)	-0.278 ***	(0.021)
CrB	-0.085 ***	(0.014)	-0.031 **	(0.016)	-0.077 ***	(0.016)	-0.069 ***	(0.017)	-0.116 ***	(0.018)
CrA	-0.129 ***	(0.018)	-0.163 ***	(0.019)	-0.173 ***	(0.019)	-0.119 ***	(0.021)	-0.168 ***	(0.022)
D2	-0.029	(0.032)	0.048	(0.035)	0.066 *	(0.037)	-0.121 ***	(0.037)	0.006	(0.039)
D3	0.018	(0.030)	0.053	(0.033)	0.073 **	(0.035)	-0.135 ***	(0.035)	0.043	(0.038)
D4	-0.037	(0.029)	-0.025	(0.032)	0.045	(0.034)	-0.147 ***	(0.034)	0.076 **	(0.037)
D5	0.308 ***	(0.116)	0.154	(0.115)	-0.078	(0.119)	-0.319	(0.152)	0.107	(0.111)
D6	0.231 ***	(0.033)	0.216 ***	(0.037)	0.249 ***	(0.038)	0.209 ***	(0.039)	0.499 ***	(0.041)
D7	-0.122 ***	(0.029)	-0.090 ***	(0.033)	-0.018	(0.034)	-0.161 ***	(0.035)	0.063 *	(0.037)
D8	-0.091 ***	(0.032)	0.006	(0.036)	-0.205 ***	(0.038)	-0.412 ***	(0.039)	-0.188 ***	(0.041)
D9	0.151 ***	(0.036)	0.167 ***	(0.039)	0.206 ***	(0.040)	0.092 **	(0.041)	0.208 ***	(0.044)
R^2	0.114		0.125		0.130		0.135		0.124	
$Adj R^2$	0.113		0.124		0.129		0.134		0.123	
$F Statistics$	136.630***		123.520***		122.320***		119.700***		110.290***	

***, **, *: 1%, 5%, 10% significance.

Table 4.11: Impact of first patent application and past performance on profitability (Δ NI/TA)

	(1)		(2)		(3)		(4)		(5)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.707***	(0.008)	-0.708***	(0.008)	-0.734***	(0.008)	-0.714***	(0.008)	-0.740***	(0.008)
TD/TA	0.001	(0.003)	0.005	(0.004)	-0.004	(0.004)	0.004	(0.004)	-0.004	(0.004)
CASH/TA	-0.044***	(0.008)	-0.047***	(0.009)	-0.028***	(0.009)	-0.036***	(0.009)	-0.015*	(0.009)
INV/S	-0.002***	(0.001)	-0.002***	(0.001)	-0.001	(0.001)	-0.003***	(0.001)	-0.002**	(0.001)
Log TA	0.007***	(0.000)	0.007***	(0.000)	0.008***	(0.000)	0.007***	(0.000)	0.008***	(0.000)
Patent	-0.001	(0.002)	-0.001	(0.002)	0.000	(0.002)	-0.001	(0.002)	-0.001	(0.002)
Rating	.	.	0.001*	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
MS	.	.	.	.	-10.264***	(3.486)	.	.	-11.925***	(3.678)
ExcReturn	.	.	.	.	0.062***	(0.002)	.	.	0.062***	(0.002)
CrD	.	.	.	.	0.016***	(0.002)	.	.	0.016***	(0.003)
CrB	.	.	.	.	0.011***	(0.002)	.	.	0.011***	(0.002)
CrA	.	.	.	.	0.018***	(0.002)	.	.	0.018***	(0.002)
D2	.	.	.	.	.	.	-0.017***	(0.004)	-0.022***	(0.004)
D3	.	.	.	.	.	.	0.011***	(0.004)	0.007*	(0.004)
D4	.	.	.	.	.	.	0.003	(0.004)	-0.003	(0.004)
D5	.	.	.	.	.	.	0.010	(0.014)	0.030**	(0.014)
D6	.	.	.	.	.	.	0.009**	(0.004)	0.001	(0.004)
D7	.	.	.	.	.	.	0.009**	(0.004)	0.005	(0.004)
D8	.	.	.	.	.	.	0.002	(0.004)	-0.003	(0.004)
D9	.	.	.	.	.	.	-0.007	(0.005)	-0.010**	(0.005)
R^2	0.240		0.239		0.268		0.243		0.272	
$Adj R^2$	0.239		0.238		0.267		0.242		0.271	
$F Statistics$	1134.47***		993.08***		619.93***		507.00***		402.70***	

***, **, *: 1%, 5%, 10% significance.

Table 4.12: Impact of first patent application and past performance on leverage (Δ TD/TA)

	(1)		(2)		(3)		(4)		(5)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.224***	(0.017)	-0.204***	(0.017)	-0.159***	(0.017)	-0.206***	(0.017)	-0.160***	(0.017)
TD/TA	-0.466***	(0.007)	-0.509***	(0.008)	-0.485***	(0.008)	-0.514***	(0.008)	-0.490***	(0.008)
CASH/TA	-0.028	(0.017)	0.015	(0.018)	-0.017	(0.018)	0.038**	(0.018)	0.003	(0.018)
INV/S	0.002*	(0.001)	0.005***	(0.001)	0.003**	(0.001)	0.005***	(0.001)	0.004***	(0.001)
Log TA	0.003***	(0.001)	0.003***	(0.001)	0.001*	(0.001)	0.001	(0.001)	0.000	(0.000)
Patent	-0.036***	(0.003)	-0.034***	(0.003)	-0.033***	(0.003)	-0.029***	(0.003)	-0.027***	(0.003)
Rating	.	.	-0.012***	(0.001)	-0.013***	(0.001)	-0.012***	(0.001)	-0.013***	(0.001)
MS	.	.	.	.	-14.300**	(7.219)	.	.	-15.556**	(7.611)
Exc Return	.	.	.	.	-0.183***	(0.005)	.	.	-0.185***	(0.005)
CrD	.	.	.	.	-0.023***	(0.005)	.	.	-0.022***	(0.005)
CrB	.	.	.	.	-0.012***	(0.004)	.	.	-0.011***	(0.004)
CrA	.	.	.	.	-0.020***	(0.005)	.	.	-0.018***	(0.005)
D2	.	.	.	.	.	.	0.014*	(0.008)	0.023***	(0.008)
D3	.	.	.	.	.	.	0.010	(0.008)	0.016**	(0.008)
D4	.	.	.	.	.	.	0.006	(0.007)	0.019***	(0.007)
D5	.	.	.	.	.	.	0.049*	(0.029)	0.041	(0.030)
D6	.	.	.	.	.	.	0.016**	(0.008)	0.035***	(0.008)
D7	.	.	.	.	.	.	-0.007	(0.007)	-0.001	(0.007)
D8	.	.	.	.	.	.	-0.044***	(0.008)	-0.037***	(0.008)
D9	.	.	.	.	.	.	0.027***	(0.009)	0.034***	(0.009)
R^2	0.173		0.176		0.218		0.181		0.224	
$Adj R^2$	0.172		0.175		0.217		0.180		0.223	
$F Statistics$	756.20***		674.46***		473.10***		347.67***		310.78***	

***, **, *: 1%, 5%, 10% significance.

Table 4.13: Impact of first patent application and past performance on liquidity (Δ CASH/TA)

	(1)		(2)		(3)		(4)		(5)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	-0.019***	(0.006)	-0.240***	(0.006)	-0.034***	(0.006)	-0.017***	(0.006)	-0.739***	(0.008)
TD/TA	-0.045***	(0.002)	-0.034***	(0.003)	-0.038***	(0.003)	-0.030***	(0.003)	-0.004	(0.004)
CASH/TA	-0.691***	(0.006)	-0.703***	(0.006)	-0.696***	(0.006)	-0.742***	(0.006)	-0.015*	(0.009)
INV/S	0.000	(0.000)	-0.001**	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.002**	(0.001)
Log TA	-0.005***	(0.000)	-0.005***	(0.000)	-0.004***	(0.000)	-0.003***	(0.000)	0.008***	(0.000)
Patent	0.005***	(0.001)	0.004***	(0.001)	0.004***	(0.002)	0.002**	(0.001)	-0.001	(0.001)
Rating	.	.	0.003***	(0.000)	0.003***	(0.001)	0.003***	(0.000)	0.001	(0.001)
MS	.	.	.	.	-1.040	(2.452)	.	.	-11.925***	(3.678)
Exc Return	.	.	.	.	0.031***	(0.001)	.	.	0.062***	(0.002)
CrD	.	.	.	.	0.002	(0.002)	.	.	0.016***	(0.003)
CrB	.	.	.	.	0.000	(0.001)	.	.	0.011***	(0.002)
CrA	.	.	.	.	0.002	(0.002)	.	.	0.017***	(0.002)
D2	.	.	.	.	.	.	0.026***	(0.003)	-0.022***	(0.004)
D3	.	.	.	.	.	.	0.005*	(0.003)	0.007*	(0.004)
D4	.	.	.	.	.	.	0.016***	(0.002)	-0.003	(0.004)
D5	.	.	.	.	.	.	0.026***	(0.009)	0.030**	(0.014)
D6	.	.	.	.	.	.	-0.005*	(0.003)	0.001	(0.004)
D7	.	.	.	.	.	.	0.005**	(0.002)	0.005	(0.004)
D8	.	.	.	.	.	.	0.049***	(0.003)	-0.003	(0.004)
D9	.	.	.	.	.	.	-0.015***	(0.003)	-0.010**	(0.005)
R^2	0.379		0.381		0.388		0.403		0.410	
$Adj R^2$	0.378		0.380		0.387		0.402		0.409	
$F Statistics$	2199.80***		1936.24***		1072.16***		1064.18***		747.93***	

***, **, *: 1%, 5%, 10% significance.

Table 4.14: Impact of first patent application and past performance on credit quality (Δ Rating)

	(1)		(2)		(3)		(4)		(5)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	0.044	(0.107)	1.177***	(0.092)	0.922***	(0.094)	1.151***	(0.092)	0.889***	(0.094)
TD/TA	1.623***	(0.043)	-0.824***	(0.045)	-0.944***	(0.045)	-0.819***	(0.045)	-0.940***	(0.045)
CASH/TA	-2.600***	(0.109)	-0.118	(0.097)	0.105	(0.097)	-0.229**	(0.099)	0.019	(0.100)
INV/S	-0.107***	(0.009)	0.035***	(0.008)	0.048***	(0.008)	0.030***	(0.008)	0.040***	(0.008)
Log TA	-0.024***	(0.005)	-0.030***	(0.004)	-0.019***	(0.004)	-0.016***	(0.004)	-0.005	(0.004)
Patent	0.081***	(0.021)	0.195***	(0.018)	0.198***	(0.018)	0.155***	(0.018)	0.156***	(0.018)
Rating	.	.	-0.662***	(0.007)	-0.658***	(0.007)	-0.669***	(0.007)	-0.664***	(0.007)
MS	.	.	.	.	-87.611**	(39.355)	.	.	-83.399**	(41.439)
Exc Return	.	.	.	.	0.953***	(0.027)	.	.	0.965***	(0.027)
CrD	.	.	.	.	0.189***	(0.027)	.	.	0.179***	(0.027)
CrB	.	.	.	.	0.087***	(0.020)	.	.	0.077***	(0.020)
CrA	.	.	.	.	0.161***	(0.025)	.	.	0.146***	(0.025)
D2	.	.	.	.	.	.	-0.179***	(0.044)	-0.254***	(0.044)
D3	.	.	.	.	.	.	-0.129***	(0.042)	-0.178***	(0.042)
D4	.	.	.	.	.	.	-0.045	(0.040)	-0.131***	(0.040)
D5	.	.	.	.	.	.	-0.591***	(0.156)	-0.349**	(0.162)
D6	.	.	.	.	.	.	-0.248***	(0.046)	-0.368***	(0.046)
D7	.	.	.	.	.	.	-0.049	(0.040)	-0.106***	(0.040)
D8	.	.	.	.	.	.	0.055	(0.045)	-0.008	(0.045)
D9	.	.	.	.	.	.	-0.487***	(0.051)	-0.533***	(0.051)
R^2	0.108		0.351		0.383		0.356		0.389	
$Adj R^2$	0.107		0.350		0.382		0.355		0.388	
$F Statistics$	436.46***		1706.29***		1052.65***		837.38***		686.44***	

***, **, *: 1%, 5%, 10% significance.

Table 4.15: Impact of first patent application and past performance on stock performance (Exc Return)

	(1)		(2)		(3)		(4)		(5)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	0.233***	(0.022)	0.224***	(0.022)	0.249***	(0.022)	0.248***	(0.022)	0.256***	(0.022)
TD/TA	0.121***	(0.009)	0.098***	(0.011)	0.099***	(0.011)	0.096***	(0.011)	0.099***	(0.011)
CASH/TA	-0.228***	(0.022)	-0.206***	(0.023)	-0.187***	(0.023)	-0.202***	(0.024)	-0.194***	(0.024)
INV/S	-0.012***	(0.002)	-0.011***	(0.002)	-0.010***	(0.002)	-0.009***	(0.002)	-0.008***	(0.002)
Log TA	-0.008***	(0.001)	-0.008***	(0.001)	-0.008***	(0.001)	-0.008***	(0.001)	-0.008***	(0.001)
Patent	0.009**	(0.004)	0.010**	(0.004)	0.008*	(0.004)	0.014***	(0.004)	0.011***	(0.004)
Rating	.	.	-0.006***	(0.002)	-0.006***	(0.002)	-0.006***	(0.002)	-0.006***	(0.002)
MS	.	.	.	.	5.443	(9.363)	.	.	26.348***	(9.864)
CrD	.	.	.	.	-0.012*	(0.006)	.	.	-0.013**	(0.006)
CrB	.	.	.	.	-0.039***	(0.005)	.	.	-0.041***	(0.005)
CrA	.	.	.	.	-0.094***	(0.006)	.	.	-0.095***	(0.006)
D2	.	.	.	.	.	.	0.050***	(0.011)	0.057***	(0.011)
D3	.	.	.	.	.	.	0.033***	(0.010)	0.037***	(0.010)
D4	.	.	.	.	.	.	0.070***	(0.010)	0.077***	(0.010)
D5	.	.	.	.	.	.	-0.111***	(0.037)	-0.144***	(0.039)
D6	.	.	.	.	.	.	0.107***	(0.011)	0.111***	(0.011)
D7	.	.	.	.	.	.	0.048***	(0.010)	0.049***	(0.010)
D8	.	.	.	.	.	.	0.027**	(0.011)	0.041***	(0.011)
D9	.	.	.	.	.	.	0.044***	(0.012)	0.039***	(0.012)
R^2	0.023		0.023		0.040		0.030		0.048	
$AdjR^2$	0.022		0.022		0.039		0.029		0.047	
$FStatistics$	77.69***		69.73***		76.73***		46.26***		57.08***	

***, **, *: 1%, 5%, 10% significance.

Table 4.16: Impact of first patent application and past performance on firm size (Δ Log TA)

	(1)		(2)		(3)		(4)		(5)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
NI/TA	0.057	(0.065)	0.074	(0.065)	-0.087	(0.067)	0.092	(0.065)	-0.071	(0.067)
TD/TA	0.058**	(0.026)	0.022	(0.032)	-0.046	(0.026)	0.026	(0.032)	-0.042	(0.032)
CASH/TA	0.467***	(0.066)	0.503***	(0.069)	0.633***	(0.069)	0.580***	(0.070)	0.687***	(0.071)
INV/S	-0.062***	(0.005)	-0.060***	(0.005)	-0.052***	(0.006)	-0.052***	(0.005)	-0.046***	(0.006)
Log TA	-0.057***	(0.003)	-0.058***	(0.003)	-0.053***	(0.003)	-0.068***	(0.003)	-0.062***	(0.003)
Patent	0.209***	(0.013)	0.211***	(0.013)	0.189***	(0.006)	0.244***	(0.013)	0.219***	(0.013)
Rating	.	.	-0.010**	(0.005)	-0.007	(0.005)	-0.006	(0.005)	-0.003	(0.005)
MS	.	.	.	.	56.937**	(28.024)	.	.	28.577	(29.473)
Exc Return	.	.	.	.	0.594***	(0.019)	.	.	0.584***	(0.019)
CrD	.	.	.	.	-0.252***	(0.019)	.	.	-0.248***	(0.019)
CrB	.	.	.	.	-0.809***	(0.014)	.	.	-0.085***	(0.014)
CrA	.	.	.	.	-0.137***	(0.018)	.	.	-0.129***	(0.018)
D2	.	.	.	.	.	.	-0.006	(0.031)	-0.029	(0.032)
D3	.	.	.	.	.	.	0.031	(0.030)	0.018	(0.030)
D4	.	.	.	.	.	.	-0.007	(0.029)	-0.037	(0.029)
D5	.	.	.	.	.	.	0.272**	(0.111)	0.308***	(0.116)
D6	.	.	.	.	.	.	0.300***	(0.032)	0.231***	(0.033)
D7	.	.	.	.	.	.	-0.092***	(0.029)	-0.122***	(0.029)
D8	.	.	.	.	.	.	-0.093***	(0.032)	-0.091***	(0.032)
D9	.	.	.	.	.	.	0.192***	(0.036)	0.151***	(0.036)
R^2	0.058		0.058		0.103		0.071		0.114	
$Adj R^2$	0.057		0.057		0.102		0.070		0.113	
$F Statistics$	221.21***		194.08***		195.25***		120.27***		138.63***	

***, **, *: 1%, 5%, 10% significance.

4.8 Conclusion

In the current environment of the increasing number of patent applications, series of attempts to reform patenting litigation and a general acknowledgment of innovation as a driver of growth, it has become crucial to assess and quantify the impact of innovation on the performance and productivity of companies. In contrast to majority of previous studies that focused on the analyses of the overall volume proxied most notably by R&D expenditure and the size of patent portfolios, we depart from the mainstream literature in three important features. Firstly, we consider priority patent applications which are among the first manifestations of the innovation. Secondly our study covers 98% of all patent applications worldwide, which makes it well adopted to the realities of globalised economy. Thirdly, we isolate and analyse the impact of the first patent associated with a company in our data. This allows to mitigate the effects of so called strategic patenting and also to quantify the effects (or a "value") of a patentable innovation in terms of profitability, capital structure, liquidity, credit rating quality, growth and stock performance. Some of these relationships such as between credit rating quality and innovation remain largely unexplored in the literature for which our analysis provides significant insights.

By comparing post and pre-patent performance for patenting companies against the control matched sample of non-patenting ones, we can eliminate the effects attributable to the differences in their distributions across years. Similarly, the results are controlled for different phases of business cycles and industries.

We do not find any significant impact of patentable innovation activities on profitability (NI/TA) which is consistent with the literature. However, in contrast to the literature explaining this phenomenon through the increase of R&D expenses which have a depressing effect on net income (NI), we argue that it might be rather the simultaneousness of growth of net income and total assets (TA) that leaves profitability unchanged.

In terms of capital structure, we confirm a significant negative effect of innovation on leverage, which in our case reaches -3% for one patent application. Combined with another result that innovation prpomotes growth we come to a conclusion that capital increase is achieved through the appreciation of own capital due to innovative patent activities rather than through borrowing.

Liquidity is positively affected by innovation which according to the literature can be the fact that patents generate additional cash flows. It is also speculated that patents reduce information asymmetries associated with R&D and lower the cost of financing. The relationship between credit quality and innovation is particularly interesting and is rarely addressed in the literature. As anticipated, the innovation that had already taken place and revealed with a priority patent application reduces the probability of default and boosts credit quality. Existing literature attributes this effect to higher returns associated with patents. We identify an additional channel improving the credit rating. It is a lower reliance on external investment due to lower leverage and higher liquidity.

Additionally, we analysed the effect of patentable innovation on stock performance which is usually the subject of a separate stream of literature but is an integral element of performance for listed companies. Markets price in revealed innovation which boosts annual stock returns compared to non-patenting companies by around 1%. This effect is confirmed in the literaure. A new result, which to our best knowledge has been reported, is that it is the only the effect of the first patent application that are significant. In other words, a priority application of a company that had not filed for a patent has the maximum positive factor and causes the strongest price reaction.

Patentable innovation is confirmed to be a significant factor of growth, increasing the growth rate of total assets by additional 5% annually on average.

Overall, we document a substantial and comprehensive impact of innovation on company performance, with our results contributing to the existing body of literature and providing new explanations.

Chapter 5

Conclusion

The main focus of this thesis is twofold. First, it examines the performance of two models, support vector machines (SVM) and logit, in bankruptcy forecasting modeling. Second, it examines the effect of technological activities information embedded in patent applications on firms' survival and financial stability. In a more detailed analysis, it also provides evidences of the impact of patent application on different aspects of the firm performance including profitability, liquidity, capital structure, size, credit quality and stock performance.

The analysis of this thesis is mainly motivated by the recent global financial crisis and its wide spread adverse impact on the world economy, which indicates the necessity of a more accurate credit rating and corporate performance assessment.

This thesis aims to provide more insight into the context of corporate bankruptcy and financial performance analysis as a crucial element for the stability of the financial markets, company survival and country's overall economic stability. Firstly, this thesis focuses on developing a corporate default prediction model with higher prediction performance compared to the commonly used models such as loigt. Secondly, against the background of a rapid rise in firms' technological activities and R&D expenditures it provides a comprehensive analysis of the impact of patent applications, as an output of R&D investments, in addition to a set of accounting measures, on firms' financial survival and economic performance.

In more details, the analysis provided in Chapter 2 of this thesis complements the existing literature by developing a bankruptcy prediction model for the listed firms in the Asian and Pacific region applying a non-linear statistical approach namely support vector machine (SVM) and compares its prediction performance with that of logit. Employing a wide range of financial ratios reflecting profitability, leverage, liquidity, efficiency, activity, size and firm's structure, the findings of this study reveal that firstly, both models select leverage and firm size indicators as the most significant predictors of default. Secondly, leverage and activity ratios present a U-shaped dependence of PD, indicating the existence of the optimal capital structure and inventory stock. Thirdly, on average SVM provides a more robust performance than logit and has a lower model risk, the results which are consistent with the previous studies (Shin et al., 2005; Kim and Sohn, 2010; Chen et al., 2011).

Chapter 3 examines the relationship between a patent application, as an output of the level of technological competence, and the corporate credit risk. Analysis of the primary patent application data allows timely use of patent data in forecasting distress and survival of firms. While it might take up to three years by a patent office for a patent application to be assessed and patent to be granted, the technological information in the application is disclosed to public only eighteen months after the the primary date of submission. Chapter 3 investigates the intuition found in the literature that a patent application can guarantee higher income by blocking competitors to have access to the new technology. Empirical analysis at firm level reveals the ability of patenting information as a measure of innovative activities in forecasting future bankruptcy is significant in the presence of the typical bankruptcy predictors, which is consistent with the previous studies (Pederzoli et al., 2013). Therefore, it provides evidences that suggest firms which are not capable in technological developments are more likely to experience financial distress.

Chapter 3, therefore, makes contribution to the innovation as well to the corporate bankruptcy literature and recommends that lenders should use technology innovation indicators such as patent application data in addition to the accounting information to assess firms' credit quality. Measuring corporate risk risk more accurately will also help to reduce both asymmetric information and financial constraints faced by firms in the external capital market.

Chapter 4 provides a further and comprehensive investigation of the impact of innovation on firms' economic performance by examining the effect of patent applications on a range of company performance characteristics, such as profitability, capital structure, stock market performance and growth. While the previous studies mainly consider the analysis of patent portfolios, Chapter 4 extends the existing literature by studying the impact of individual priority patent applications on firms' economic performance. The empirical results of this study indicate that patent applications reflecting the companies' R&D investment and subsequent innovations are reliably correlated with the future performance of firms. The empirical findings of this chapter suggest higher capitalisation, increased liquidity, a lower leverage and higher stock return for patenting firms. The explanation on the positive effect of patenting activities on firm performance is related to the direct and indirect benefits of patents, such as (i) an increase in cash flow due to utilisation of the new technology which is exclusive to the firm; (ii) additional income generated through licensing or trading the patent with other firms via cross-licensing; (iii) using patents as bargaining power to negotiate with other firms to get access to new technologies; (iv) expanding market power internationally and enhancing the firm's reputation.

Furthermore, this study indirectly confirms some findings in the previous studies in terms of impact of patent on county's economic performance. Patents as an output indicator of innovation and technological activities, drive a country's export. Some empirical studies find significant correlation between the patenting activities of countries and their economic success in both national and international markets. Therefore, developing technological competence contributes to economic performance of the country as a whole (Frietsch et al., 2014).

With regards to policy implication, the empirical findings of this thesis on the importance of patenting on overall firms financial survival and economic performance supported by the evidences from the literature, suggest more governmental and regulatory assistance such as financial help for R&D investments and legal and financial support during the patenting process, especially for small and medium size firms (SMEs). Compared to the international and larger firms which file more patents then their small and medium size counterparts (Neuhäusler, 2012), SMEs have less financial resources (Frietsch et al., 2013) to finance their innovative activities. At the same time, SMEs are seen as an important source of innovation and employment growth in the economy.

Appendices

Appendix A

Logit Model

The econometric model of conditional logit analysis in bankruptcy forecasting was first introduced to avoid well-known problems associated with Discriminant Analysis (DA) using vector of predictors. Some of these problems are the assumptions of the distributional properties of the vectors, such as normally distributed predictors and the same variance-covariance matrices of the predictors for both failed and non-failed groups. Conditional logit analysis estimates the probability a firm defaults within a specified time horizon, using a set of indicators and given that the firm belongs to a pre-specified group (Ohlson, 1980). Therefore, the probability of default depends conditionally on the predictors. Another advantage of logit is that the output is probability of default (PD) and therefore no score needs to be converted to a probabilistic measure.

Let X_i represent a vector of predictors for the ith observation, β a set of coefficients to be estimated and $P(X_i, \beta)$ probability of default for a given X_i and β. P is a probability function with with the output $0 \leq P \leq 1$ reflected by the binary sample of defaulting and non-defaulting firms. In order to estimate the coefficients in the β vector the following form of log-likelihood function is maximised.

$$L(\beta) \equiv \sum_{i \in S_D} log P(X_i, \beta) + \sum_{i \in S_{ND}} log(1 - P(X_i, \beta))$$

The index S_D represents the defaulting group and S_{ND} non-defaulting group. The probability function P is the logistic distribution indicated below;

$$P = (1 + exp(-y_i))^{-1}$$

Where,

$$y_i \equiv \sum_i \beta_j X_{ij} = \beta^{'} X_i$$

Which implies firstly, as y increases P increases and secondly, y equals to $log[P/(1-P)]$. Therefore, the model is fairly easy to implement and interpret.

Appendix B

Conversion of Scores into Probability of Default (PD)

The conversion of rating scores into PDs provides us with a link to the existing rating classes reported by rating agencies such as Moody's and S&P. In the Logistic model a sigmoid function is applied to estimate PD assuming the logistic distribution of the latent variable. However, such an assumption is often not compatible with reality. In general the company score, as it is computed by the SVM or logit, defines the distance between companies in terms of PD: the lower the difference in scores, the closer are companies. If a company has a higher score, it lies farther from successful companies and, therefore, its PD should be higher. This means that the dependence between scores and PDs is assumed to be monotonic. No further assumptions about the form of this dependence will be made in contrast to the already mentioned logit model with a prespecified functional transformation from the score to PD.

The conversion procedure consists of the estimation of PDs for the observations of the training set with a subsequent monotonisation (step one and two) and the computation of a PD for a new company (step three).

Step one is the estimation of PDs for the companies of the training set. This is done using standard smoothing techniques in order to preliminary evaluate PDs for all $i = 1, 2, \ldots, n$ observations of the training set:

$$\widetilde{PD}(z) = \frac{\sum_{i=1}^{n} w(z - z_i) I(y_i = 1)}{\sum_{i=1}^{n} w(z - z_i)}, \tag{B.0.1}$$

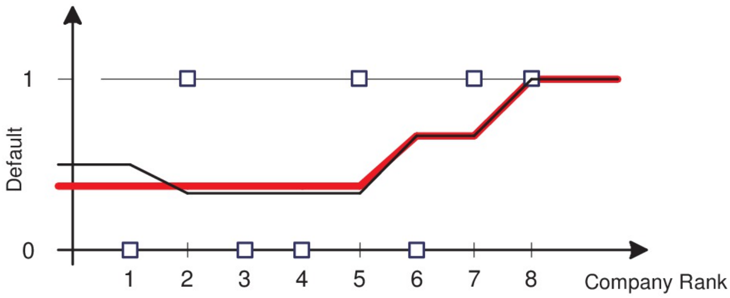
where $w(z - z_i) = \exp\{(z - z_i)^2/2h^2\}$. The rank of the i-th company $z_i = Rank\{f(x_i)\}$ can be 1, 2, 3, ... up to n depending on its score $f(x_i)$; the higher the score is, the higher is the rank. h is a bandwidth, in our case $h = 0.09n$. The smaller is the bandwidth, the smoother is $\widetilde{PD}(z)$. When $h \to 0$ no smoothing is performed and all $\widetilde{PD}(z_i)$, $i = 1, 2, \ldots, n$, will be either 1 or 0; when $h \to \infty$, all $\widetilde{PD}(z_i)$ will have the same value equal to the average probability of default for the training set.

Using the company rank z instead of the score $f(x)$ a k-NN smoother is obtained with Gaussian weights $\frac{w(z-z_i)}{\sum_{j=1}^{n} w(z-z_j)}$ which decay gradually as $|z - z_i|$ grows. This differs from the most commonly used k-NN smoother that relies on the uniform weights $\frac{1}{k} I(|z - z_i| < \frac{k}{2} + 1)$.

The preliminary PDs evaluated at step one are not necessarily a monotonic function of the score. This is due to the fact that companies with close scores may have for different reasons a non-concordant binary survival indicator y. The monotonisation of $\widetilde{PD}(z_i)$, $i = 1, 2, \ldots, n$ is achieved at step two using the Pool Adjacent Violator (PAV) algorithm (Barlow et al., 1972). Figure B.1 illustrates the workings of the algorithm. The companies are ordered according to their rank and have here the indicator $y = 1$ for insolvent and $y = 0$ for solvent companies. The thin line denotes the PDs estimated using the k-NN method with uniform weights and $k = 3$. At the interval between the observations with rank 1 and 2 monotonicity is violated and is corrected with the PAV algorithm. The bold line shows PDs after monotonisation.

The PAV algorithm solves the following optimisation problem: given data $\{z_i, y_i\}_{i=1}^{n}$ with $z_1 \le z_2 \le \ldots \le z_n$ find the monotonic increasing function $m(z_i)$, i.e. $m(z_1) \le m(z_2) \le \ldots \le m(z_n)$ that minimises $\sum_{i=1}^{n} \{y_i - m(z_i)\}^2$. The solution to this problem is pooling (averaging) the adjacent observations that are violating monotonicity. The PAV acronym comes from this property. Mammen (1991) has shown that one can equivalently start with the PAV step and then

Figure B.1: Monotonisation of PDs with the pool adjacent violator algorithm.



Note: The thin line denotes PDs estimated with the k-NN method with uniform weights and $k = 3$ before monotonisation and the bold line after monotonisation. Here $y = 1$ for insolvencies, $y = 0$ for solvent companies.

smooth with a Nadaraya-Watson kernel estimator (Nadaraya (1964)).

As a result monotonised probabilities of default $PD(x_i)$ is obtained for the observations of the training set. A PD for any observation x of the testing set is computed by interpolating PDs for two adjacent, in terms of the score, observations from the training set. If the score for x lies beyond the range of the scores of the training set, then $PD(x)$ is set equal to the score of the first neighbouring observation of the training set.

Appendix C

Estimating Rating Applying logit Model

In order to assign a rating class to each firms, first we estimate the probability of default (PD) for each firm using a logit regression. For details of the logit regression see Appendix A.

In our analysis, defaulting group S_D represents the firms which filed at least one credit event within two years period from the date of the financial report. Credit event means: liquidation under Chapter 7 of the US Bankruptcy Code, restructuring under Chapter 11 of the US Bankruptcy Code, default on coupon or principle payments and covenant. S_{ND} represents the firms with no credit event record. In our data set from 444,392 observations with financial information 11,424 (2.57%) observations are labelled as distressed and 432,968 (97.43%) as solvent.

We specify X_i a vector of 10 accounting ratios which were identified by a forward variable selection approach as the most significant factors amongst a wide range of indicators. These 10 indicators are: Total Debt/Total Assets, Current Assets/Current Liabilities, Operating Income/Total Assets, Working Capita/Total Assets, CASH/Total Assets, CASH/Current Liabilities, Current Liabilities/Total Liabilities, Account Receivables/Sales, Inventory/Sales and Net Income/Total Assets.

After estimating PD for each firm, we map each PD to a Moody's rating class

Table C.1: Rating classes mapped to Moody's historical Average Cumulative Default Rates (ACDR)

Moody's Rating Classes	Moody's ACDR	PD intervals	Rating Classes
Aaa	0.000%	$0.000\% \leq PD < 0.019\%$	17, 18 19
Aa	0.019%	$0.019\% \leq PD < 0.095\%$	14, 15, 16
A	0.095%	$0.095\% \leq PD < 0.506\%$	11, 12, 13
Baa	0.506%	$0.506\% \leq PD < 3.222\%$	8, 9, 10
Ba	3.222%	$3.222\% \leq PD < 11.298\%$	5, 6, 7
B	11.298%	$11.298\% \leq PD < 30.509\%$	2, 3, 4
Caa–C	30.509%	$PD \geq 30.509\%$	1

1. Moody's historical Average Cumulative Default Rates (ACDR) are derived from Monthly Cohorts: 1970–2006 for 2 year time horizon and represent mean of the bootstrapped samples for each class.
2. In order to have higher granularity of the rating classes, the ACDR between each rating class is divided into three intervals and each interval is assigned to a rating scale. Then we mapped estimated PD for each firm to the relevant interval to derive its representative rating scale, i.e. 1 for the least stable companies (C) and 19 for the safest ones (Aaa).

which have been defined based on Moody's historical average cumulative default rates. In order to have higher granularity of the rating classes, we have divided each Moody's rating class into three classes. As a result we have defined 19 rating scales with 1 for the least stable companies (C) and 19 for the safest ones (Aaa). Details of our rating class variable mapped against Moody's rating classes is provided in Table C.1.

Bibliography

Aboulnasr, K., O. Narasimhan, E. Blair, and R. Chandy, 2008: Competitive response to radical product innovations. *Journal of Marketing*, **72**(3), 94–110.

Aghion, P. and P. Bolton, 1992: An "incomplete contracts" approach to financial contracting. *Review of Economic Studies*, **59**(3), 473–494.

Alegre, J., R. Lapiedra, and R. Chiva, 2006: A measurement scale for product innovation performance. *European Journal of Innovation Management*, **9**(9), 333–346.

Altman, E., 1968: Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, **23**(4), 589–609.

Altman, E., R. Haldeman, and P. Narayanan, 1977: Zeta analysis: a new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, **1**(1), 29–54.

Altman, E. and A. Saunders, 2001: An analysis and critique of the bis proposal on capital adequacy and ratings. *Journal of Banking & Finance*, **25**(1), 25–46.

Andries, P. and D. Faems, 2013: Patenting activities and firm performance: Does firm size matter? *The Journal of Product Innovation Management*, **30**(6), 1089–1098.

Arora, A., A. Fosfuri, and A. Gambardella, 2004: *The Economics of Innovation and Corporate Strategy*. The MIT Press.

Baesens, B., T. V. Gestel, S. Viaene, M. Stepanova, J. Suykens, and J. Vanthienen, 2003: Benchmarking state-of-the-art classification algorithms for credit scoring. *Journal of the Operational Research Society*, **54**(6), 627–635.

Bagorogoza, J. and A. D. Waal, 2010: The role of knowledge management in creating and sustaining high performance organisations the case of financial institutions in uganda. *World Journal of Enterprenuership Management and Sustainable Development*, **6**(4), 307–323.

Baker, L. J. A. and H. Ahmad, 2010: Assessing the relationship between firm resources and product innovation performance. *Business Process Management Journal*, **16**(3), 420–435.

Barlow, R. E., J. M. Bartholomew, J. M. Bremmer, and H. D. Brunk, 1972: *Statistical inference under order restrictions*. John Wiley & Sons, New York, NY.

Bayus, B. L., G. Erickson, and R. Jacobson, 2003: The financial rewards of new product introductions. *Management Science*, **49**(2), 197–210.

BCBS, 2003: Basel Committee on Banking Supervision: the New Basel Capital Accord, third consultative paper. *http://www.bis.org/bcbs/cp3ov.pdf*.

Beaver, G., 2002: *Small Business, Entrepreneurship and Enterprise Development*. Pearson Education Ltd, United Kingdom.

Beaver, W., 1966: Financial ratios as predictors of failures. *Journal of Accounting Research* 71–111. Empirical Research in Accounting: Selected Studies.

Becchetti, L. and J. Sierra, 2003: Bankruptcy risk and productive efficiency in manufacturing firms. *Journal of Banking & Finance*, **27**(11), 2099–2120.

Belenzon, S. and A. Patacconi, 2013: Innovation and firm value: An investigation of the changing role of patents, 1985-2007. *Research Policy*, **42**(8), 1496–1510.

Bellotti, T. and J. Crook, 2009: Credit scoring with macroeconomic variables using survival analysis. *Journal of the Operational Research Society*, **60**(12), 1699–1707.

Bessen, J. and M. J. Meurer, 2005: The patent litigation explosion, unpublished working paper. *Boston University*.

Bhagat, S., J. A. Brickley, and J. L. Coles, 1994: The costs of inefficient bargaining and financial distress: Evidence from corporate lawsuits. *Journal of Financial Economics*, **35**(2), 221–247.

Bharath, S. T. and T. Shumway, 2008: Forecasting default with the merton distance to default model. *Review of Financial Studies*, **21**(3), 1339–1369.

Blind, K., K. Cremers, and E. M. Mueller, 2009: The influence of strategic patenting on companies'patent portfolios. *Research Policy*, **38**(2), 428–436.

Blind, K., J. Edler, R. Frietsch, and U. Schmoch, 2006: Motives to patent: Empirical evidence from germany. *Research Policy*, **35**(5), 655–672.

Bloom, N. and J. V. Reenen, 2002: Patents, real options and firm performance. *The Economic Journal*, **112**(478), C97–C116.

Blundell, R., R. Griffith, and J. V. Reenen, 1999: Market share, market value and innovation in a panel of british manufacturing firms. *The Review of Economic Studies*, **66**(3), 529–554.

Bonfim, D., 2009: Credit risk drivers: Evaluating the contribution of firm level information and macroeconomic dynamics. *Journal of Banking & Finance*, **33**(2), 281–299.

Breslow, N. E., 1974: Covariance analysis of censored survival data. *Biometrics*, **30**(1), 89–99.

Bryant, S. M., 1997: A case-based reasoning approach to bankruptcy prediction modeling. *Intelligent system in accounting, Finance and Management*, **6**(3), 195–214.

Cainelli, G., R. Evangelista, and M. Savona, 2006: Innovation and economic performance in services: a firm-level analysis. *Cambridge Journal of Economics*, **30**(3), 435–458.

Calantone, R. J., S. K. Vickery, and C. Droge, 1995: Business performance and strategic new product development activities: An empirical investigation. *Journal of Product Innovation Management*, **12**(3), 214–223.

Camison, C. and A. V. Lopez, 2010: An examination of the relationship between manufacturing flexibility and firm performance: The mediating role of innovation. *International Journal of Operations & Production Management*, **30**(8), 853–878.

Campbell, J. Y., J. Hilscher, and J. Szilagyi, 2008: In search of distress risk. *Journal of Finance*, **63**(6), 2899–2939.

Capon, N., J. U. Farley, and S. M. Hoenig, 1990: A meta-analysis of financial performance. *Management Science*, **36**(10), 1143–1160.

Carey, M. and M. Hrycay, 2001: Parametrizing credit risk models with rating data. *Journal of Banking & Finance*, **25**(1), 197–270.

Carpenter, R. and B. Petersen, 2002: Capital market imperfections, high-tech investment, and new equity financing. *Economic Journal*, **112**(477), 54–72.

Chava, S. and R. A. Jarrow, 2008: Bankruptcy prediction with industry effect. *Review of Finance*, **8**(4), 537–569.

Chen, S., W. K. Härdle, and R. A. Moro, 2011: Modeling default risk with support vector machines. *Quantitative Finance*, **11**(1), 135–154.

Chen, Y. S. and K. C. Chang, 2010: Correlated default risks and bank regulations. *Technology Analysis & Strategic Management*, **22**(2).

Cincera, M., 1997: Patents, r&d, and technological spillovers at the firm level: some evidence from econometric count models for panel data. *Journal of Applied Econometrics*, **12**(3), 265–280.

Comanor, W. S. and F. M. Scherer, 1969: Patent statistics as a measure of technical change. *Journal of Political Economy*, **77**(3), 392–398.

Cox, D. R., 1972: Regression models and life tables. *Journal of the Royal Statistical Society.Series B (Methodologycal)*, **34**(2), 187–220.

Czarnitzki, D. and K. Kraft, 2010: On the profitability of innovative assets. *Applied Economics*, **42**(15), 1941–1953.

Dellepiane, U., M. D. Marcantonio, E. Laghi, and S. Renzi, 2015: Bankruptcy prediction using support vector machines and feature selection during the recent financial crisis. *International Journal of Economics and Finance*, **7**(8), 182.

Deng, Z., L. Baruch, and F. Narin, 1999: Science and technology as predictors of stock perfromance. *Financial Analysts Journal*, **55**(3).

Deng, Z., B. Lev, and F. Narin, 1999: Science and technology as predictors of stock performance. *Financial Analyst Journal*, **55**(3), 20–32.

Dichev, I. D., 1998: Is the risk of bankruptcy a systematic risk? *Journal of Finance*, **53**(3), 1131–1147.

Dimitras, A., R. Slowinski, R. Susmaga, and C. Zopounidis, 1999: Business failure prediction using rough sets. *European Journal of Operational Research*, **114**(2), 263–280.

Dobbs, M. and R. T. Hamilton, 2006: Small business growth: Recent evidence and new directions. *International Journal of Entrepreneurial Behaviour and Research*, **13**(5), 296–322.

Duan, J. C., J. Sun, and T. Wang, 2012: Multiperiod corporate default prediction– a forward intensity approach. *Journal of Econometrics*, **170**(1), 191–209.

Efron, B. and R. J. Tibshirani, 1993: *An introduction to the bootstrap*. Chapman & Hall/CRC, New York, NY.

Eisdorfer, A. and P. H. Hsu, 2009: Innovate to survive: The effect of technology competition on corporate bankruptcy. *University of Connecticut*.

Eisdorfer, A. and P. H. Hsu, 2011: Innovate to survive: The effect of technology competition on corporate bankruptcy. *Financial Management*, **40**(4), 1087–1117.

Elmer, P. J. and D. M. Borowski, 1988: An expert system approach to financial analysis: The case of s&l bankruptcy. *Financial Management*, **17**(3), 66–76.

Ernst, H., 1995: Patenting strategies in the german mechanical engineering industry and their relationship to firm performance. *Technovation*, **15**(4), 225–240.

Ernst, H., 2001: Patent applications and subsequent changes of performance: Evidence from time-series cross-section analysis on the firm level. *Research Policy*, **30**(1), 134–157.

Ernst, H., 2003: Patent information for strategic technology management. *World Patent Information*, **25**(3), 233–242.

Espallardo, M. H. and E. D. Ballester, 2009: Product innovation in small manufacturers, market orientation and the industrys five competitive forces: Empirical evidence from spain. *European Journal of Innovation Management*, **12**(4), 470–491.

Falkenstein, E., A. Boral, and L. Carty, 2000: *RiskCalc for private companies: Moody's default model, Report Number: 56402*. Moody's Investors Service, Inc., New York.

Fernandes, J. E., 2005: Corporate credit risk modeling: Quantitative rating system and probability of default estimation. *http://pwp.netcabo.pt/jed_fernandes/JEF_CorporateCreditRisk.pdf*.

Fitzpatrick, P., 1932: *A comparison of the ratios of successful industrial enterprises with those of failed companies*. The Accounting Publishing Company.

Fletcher, R., 1987: *Practical methods of optimization.* John Wiley and Sons, Inc., 2nd edition.

Forker, L. B., S. K. Vickery, and C. L. M. Droge, 1996: The contribution of quality to business performance. *International Journal of Operations and Production Management*, **16**(8), 44–62.

Foster, L. and J. Ramser, 1931: *A Demonstration of Ratio Analysis. Bulletin No. 40.* University of Illinois, Bureau of Business Research, Urbana, Illinois.

Franzen, L., K. Rodgers, and T. Simin, 2007: Measuring distress risk: The effect of R&D intensity. *Journal of Finance*, **62**(6), 2391–2968.

Friedman, C., 2002: Creditmodel technical white paper. discussion paper, Standard & Poor's.

Frietsch, R., P. Neuhäusler, T. Jung, and B. V. Looy, 2014: Patent indicators for macroeconomics growth-the value of patents estimated by export volume. *Technovation*, **34**(9), 546–558.

Frietsch, R., P. Neuhäusler, and O. Rothengatter, 2013: Sme patenting – an empirical analysis in nine countries. *Fraunhofer ISI Discussion Papars Innovation Systems and Policy Analysis.*

Fry, R., Y. L. Hsiao, and C. Tang, 2010: A comparison of seven crises. *CAMA, RSE, Australian National University.*

Frydman, H., E. Altman, and D.-L. Kao, 1985: Introducing recursive partitioning for financial classification: The case of financial distress. *The Journal of Finance*, **40**(1), 269–291.

Gale, D., H. W. Kuhn, and A. W. Tucker, 1951: *Linear programming and the theory of games, in activity analysis of Production and Allocation, T. C. Koopmans (ed.).* John Wiley & Sons, New York, NY, 317–329.

Gambardella, A., D. Harhoff, and B. Verspagen, 2008: The value of european patents. *CEPR Discussion Paper*, (DP6848).

Gambardellaa, A., P. Giurib, and A. Luzzi, 2007: The value of european patents. *Research Policy*, **36**(8), 1163–1183.

Garleanu, N., L. Kogan, S. Panageas, and W. Kohler, 2009: The demographics of innovation and asset returns. *University of California at Berkeley.*

Garrigos-Simon, F. J. and D. P. Marques, 2004: Competitive strategies and firm performance: A study in the spanish hospitality sector. *Management Research*, **2**(3), 251–269.

Garrigos-Simon, F. J., D. P. Marques, and Y. Narangajavana, 2005: Competitive strategies and performance in spanish hospitality firms. *International Journal of Contemporary Hospitality Management*, **17**(1), 22–38.

Garvin, D. A., 1987: Competing on the eight dimensions of quality. *Harvard Business Review*, **65**(6), 101–109.

Geroski, P., S. Machin, and J. V. Reenen, 1993: The profitability of innovating firms. *The RAND Journal of Economics*, **24**(2), 198–211.

Glennon, D. and P. Nigro, 2005: Measuring the default risk of small business loans: A survival analysis approach. *Journal of Money, Credit and Banking*, **37**(5), 923–947.

Grant, R. M., A. P. Jammine, and H. Thomas, 1988: Diversity, diversification, and profitability among british manufacturing companies 1972-1984. *Academy of Management Journal*, **31**(4), 771–801.

Greenwood, J. and B. Jovanovic, 1999: The information-technology revolution and the stock market. *American Economic Review*, **89**(2), 116–122.

Griffin, J. M. and M. L. Lemmon, 2002: Book to market equity, distress risk and stock returns. *Journal of Finance*, **57**(5), 2317–2336.

Griliches, Z., 1990: Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, **28**(4), 1661–1707.

Grunert, J., L. Norden, and M. Weber, 2005: The role of non-financial factors in internal rredit ratings. *Journal of Banking & Finance*, **29**(2), 509–531.

Guellec, D. and B. V. P. de la Potterie, 2001: The internationalisation of technology analysed with patent data. *Research Policy*, **30**(8), 1253–1266.

Hall, B. H., 1993: The stock market's valuation of r&d investment during the 1980's. *American Economic Review*, **83**(2), 259–264.

Hall, B. H., 2005: Exploring the patent explosion. *Journal of Technology Transfer*, **30**(2), 35–48.

Hall, B. H., A. Jaffe, and M. Trajtenberg, 2005: Market value and patent citation. *The RAND Journal of Economics*, **36**(1), 16–38.

Hall, B. H., G. Thoma, and S. Torrisi, 2007: The market value of patents and R&D: Evidence from European firms. *NBER Working paper*.

Han, J. K., N. Kim, and R. K. Srivastava, 1998: Market orientation and organizational performance: Is innovation a missing link? *Journal of Marketing*, **62**(4), 30–45.

Hand, D., 2006: Classifier technology and the illusion of progress. *Statistical Science*, **21**(1), 1–14.

Helmers, C. and M. Rogers, 2010: Innovation and the survival of new firms in the uk. *Review of Industrial Organisation*, **36**(3), 227–248.

Hobijin, B. and B. Jovanovic, 2001: The information-technology revolution and the stock market: Evidence. *American Economic Review*, **91**(5), 1203–1220.

Hsu, F. J., Y. C. Chen, and W. C. Wang, 2013: An empirical study on the relationship between r&d and financial performance. *Journal of Applied Finance & Banking*, **3**(5), 107–119.

Hsu, P. H., 2009: Technological innovations and aggregate risk premiums, forthcoming. *Journal of Financial Economics*, **94**(2), 264–279.

Im, J., D. W. Apley, C. Qi, and X. Shan, 2012: A time-dependent proportional hazards survival model for credit risk analysis. *Journal of the Operational Research Society*, **63**, 306–321.

Kamiyama, S., J. Sheehan, and C. Martinez, 2006: Valuation and exploiting of intellectual property. *STI working paper,Paris,OECD*.

Kennedy, P., 2008: *A Guide to Econometrics*. 6th edition, Blackwell Publishing, Malden.

Kim, H. S. and S. Y. Sohn, 2010: Support vector machines for default prediction of smes based on technology credit. *European Journal of Operational Research*, **201**(4), 838–846.

Kim, S. and K. Huarng, 2011: Winning strategies for innovation and high-technology products management. *Journal of Business Research*, **64**(11), 1147–1150.

Krager, J. and J. A. Parnell, 1996: Strategic planning emphasis and planning satisfaction in small firms: An empirical investigation. *Journal of Business Strategies*, **13**(1), 42–64.

Lacerda, A. I. and R. A. Moro, 2008: Analysis of the predictors of default for portuguese firms. Working paper 22, Banco de Portugal.

Lanjouw, J. O. and J. Lerner, 2001: Tilting the table? the use of preliminary injunctions. *Journal of Law and Economics*, **44**(2), 573–603.

Lee, K. C., I. Han, and Y. Kwon, 1996: Hybrid neural network models for bankruptcy prediction. *Decision Support Systems*, **18**(1), 63–72.

Lerner, J., 1994: The importance of patent scope: an empirical analysis. *The RAND Journal of Economics*, **25**(2), 319–333.

Lerner, J., 1995: Patenting in the shadow of competitors. *Journal of Law and Economics*, **38**(2), 463–495.

Lichtenthaler, U., 2009: The role of corporate technology strategy and patent portfolios in low-, medium- and high-technology firms. *Research Policy*, **38**(3), 559–569.

Lin, C. H., C. H. Peng, and D. T. Kao, 2008: The innovativeness effect of market orientation and learning orientation on business performance. *International Journal of Manpower*, **29**(8), 752–772.

Löffler, G. and A. Maurer, 2011: Incorporating the dynamics of leverage into default prediction. *Journal of Banking & Finance*, **35**(12), 3351–3361.

Lumpkin, G. T. and G. G. Dess, 2001: Linking two dimensions of entrepreneurial orientation to firm performance: The moderating role of environment and industry life cycle. *Journal of Business Venturing*, **16**(5), 429–51.

Mahoney, J. T., 1995: The management of resources and the resource of management. *Annals of Statistics*, **33**(2), 91–101.

Malhotra, R. and D. Malhotra, 2002: Differentiating between good credits and bad credits using neuro-fuzzy systems. *European Journal of Operational Research*, **136**(1), 190–211.

Mammen, E., 1991: Estimating a smooth monotone regression function. *Annals of Statistics*, **19**(2), 724–740.

Mann, R. J. and T. W. Sager, 2007: Patents, venture capitals, and software start-ups. *Research Policy*, **36**(2), 193–208.

Manning, M. J., 2004: Exploring the relationship between credit spreads and default probabilities. *Working Paper No. 225, Bank of England.*

Markham, I. S. and C. T. Ragsdale, 1995: Combining neural networks and statistical predictions to solve the classification problem in discriminant analysis. *Decision Science*, **26**(2), 229–242.

Martens, D., B. Baesens, T. van Gestel, and J. Vanthienen, 2006: Comprehensible credit scoring models using rule extraction from support vector machines. working paper 878283, Social Science Research Network.

Martin, D., 1977: Early warning of bank failure: A logit regression approach. *Journal of Banking & Finance*, **1**(3), 249–276.

Mercer, J., 1909: Functions of positive and negative type and their connection with the theory of integral equations. *Philosophical Transactions of the Royal Society of London*, **209**, 415–446.

Merton, R. C., 1974: On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, **29**(2), 449–470.

Modina, M. and F. Pietrovito, 2014: A default prediction model for italian smes: The relevance of capital structure. *Applied Financial Economics*, **24**(23), 1537–1554.

Myers, S., 1977: Determinants of corporate borrowing. *Journal of Financial Economics*, **5**(2), 147–175.

Nadaraya, E. A., 1964: On estimating regression. *Theory of Probability and its Applications*, **9**(1), 141–142.

Narin, F., E. Noma, and R. Perry, 1987: Patents as indicators of corporate technological strength. *Research Policy*, **16**(2), 143–155.

Neuhäusler, P., 2012: The use of patents and informal appropriation mechanisms–differences between sectors and among companies. *Technovation*, **32**(12), 681–693.

Neuhäusler, P., C. B. Frey, and K. Blind, 2011: Patent information and corporate credit rating: An emprical study of patent valuation by credit rating agencies. *Decision Makers Conference, USPTO, Alexandria, VA.*

O'Brien, J. P., 2003: The capital structure implications of pursuing a strategy of innovation. *Strategic Management Journal*, **24**(5), 415–431.

Odders-White, E. R. and M. J. Ready, 2006: Credit ratings and stock liquidity. *Review of Financial Studies*, **19**(1), 119–157.

Ohlson, J. A., 1980: Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, **18**(1), 109–131.

Pakes, A., 1985: On patents, R&D, and the stock market rates of returns. *Journal of Political Economy*, **93**(2), 390–409.

Pederzoli, C., G. Thoma, and C. Torricelli, 2013: Modelling credit risk for innovative smes: the role of innovation measuress. *Journal of Financial Services Research*, **44**(1), 111–129.

Peteraf, M. A., 1993: The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal*, **14**(3), 179–191.

Platt, J., 1998: Sequential minimal optimization: A fast algorithm for training support vector machines. technical report msr-tr-98-14, Microsoft Research.

Qui, J. and C. Wan, 2015: Technology spillovers and corporate cash holdings. *Journal of Financial Economics*, **115**(2), 558–573.

Roberts, P. W. and R. Amit, 2003: The dynamics of innovative activity and competitive advantage: The case of australian retail banking, 1981 to 1995. *Organization Science*, **14**(2), 107–122.

Rosli, M. M. and S. Sidek, 2013: The impact of innovation on the performance of small and medium manufacturing enterprises: Evidence from malaysia. *Journal of Innovation Management in Small & Medium Enterprise*, **2013**(1), 867–887.

Sandvik, I. L. and K. Sandvik, 2003: The impact of market orientation on product innovativeness and business performance. *International Journal of Research in Marketing*, **20**(4), 255–376.

Sarkar, S. and R. S. Sriram, 2001: Bayesian models for early warning of bank failure. *Management Science*, **47**(11), 1457–1475.

Scherer, F. M., 1965: Corporate inventive output, profits and growth. *The Journal of Political Economy*, **73**(3), 290–297.

Schumpeter, J. A., 1934: Theory of economic development: An enquiry into profits, capital, interest and the business cycle. *Cambridge, MA, Harvard University Press.*

Shin, K. S., T. S. Lee, and H. J. Kim, 2005: An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications*, **28**(1), 127–135.

Shumway, T., 2001: Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business*, **74**(1), 101–124.

Smith, K., 2005: *Measuring Innovation.* The Oxford Handbook of Innovation. J. Fagerberg, Mowery, David C., Nelson, Richard R. Oxford, Oxford University Press.

Sridhar, S., S. Narayanan, and R. Srinivasan, 2014: Dynamic relationships among r&d, advertising, inventory and firm performance. *Journal of Academy of Marketing Science*, **42**(3), 277–290.

Tavitiyaman, P., H. Q. Zhang, and H. Qu, 2012: The effect of competitive strategies and organizational structure on hotel performance. *International Journal of Contemporary Hospitality Management*, **21**(1), 140–159.

Tikhonov, A. N., 1963: *On solving ill-posed problem and method regularization.* Doklady Akademii Nauk SSSR 151, 501–504.

Tikhonov, A. N. and V. Y. Arsenin, 1977: *Solution of ill-posed problems.* W. H. Winston, Washington, DC.

Toivanen, O., P. Stoneman, and D. Bosworth, 2002: Innovation and the market value of the uk firms, 1989–1995. *Oxford Bulletin of Economics and Statistics*, **64**(1), 39–61.

Trau, F., 1996: Why do firms grow? *Working Paper*, **26, Roma, Italy**.

Vapnik, V., 1995: *The nature of statistical learning theory.* Springer, New York, NY.

Vapnik, V., 1998: *Statistical Learning Theory.* Springer, New York, NY.

Varis, M. and H. Littunen, 2010: Types of innovation, sources of information and performance in entrepreneurial smes. *European Journal of Innovation Management*, **13**(2), 128–154.

Vincente-Lorente, J. D., 2001: Specificity and opacity as resource-based determinants of capital structure: Evidence for spanish manufacturing firms. *Strategic Management Journal*, **22**(2), 157–177.

Wernerfelt, B., 1984: A resource-based view of the firm. *Strategic Management Journal*, **5**(2), 171–180.

Weyl, H., 1928: *Gruppentheorie und quantenmechanik.* Hirzel, Leipzig.

Wiginton, J., 1980: A note on the comparison of logit and discriminant models of consumer credit behaviour. *Journal of Financial and Quantitative Analysis*, **15**(3), 757–770.

Wilbon, A., 2002: Predicting survival of high-technology initial public offerings. *Journal of High Technology Management Research*, **13**(1), 127–141.

Wilcox, J. W., 1971: A simple theory of financial ratios as predictors of failure. *Journal of Accounting Research*, **9**(2), 389–395.

Winakor, A. and R. Smith, 1935: *Changes in the financial structure of unsuccessful industrial corporations. Bulletin No. 51.* University of Illinois, Bureau of Business Research, Urbana, Illinoiss.

WIPO, 2011a: World intellectual property report on the changing face of innovation in 2011. *Geneva, WIPO.*

WIPO, 2011b: World intellectual property report survey on patenting strategies in 2009 and 2010. *Geneva, WIPO.*

Wolff, J. and T. Pett, 2006: Small-firm performance: Modeling the role of product and process improvements. *Journal of Small Business Management*, **44**(2), 268–284.

Zahra, S. A., 2008: Being entrepreneurial and market driven: Implications for company performance. *Journal of Strategy and Management*, **1**(2), 125–142.

Zahra, S. A. and S. R. Das, 1993: Innovation strategy and financial performance in manufacturing companies: An empirical study. *Product and Operations Management*, **2**(1), 90–101.

Zavgren, C. V., 1983: The prediction of corporate failure: The state of the art. *Journal of Accounting Literature*, **2**, 1–38.

Zmijewski, M. E., 1984: Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, **22**, 59–82.