CRAFIELD UNIVERSITY
Naif A. Al Baz

MODELLING CREDIT RISK FOR SMES IN SAUDI ARABIA

Cranfield School of Management
Doctor of Business Administration
Academic Year: 2016–2017
Supervisors: Professor Huainan Zhao
Dr. Vineet Agarwal
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This thesis is submitted in partial fulfillment of the requirements for the degree of Doctor of Business Administration

ABSTRACT

The Saudi Government's 2030 Vision directs local banks to increase and improve credit for the Small and Medium Enterprises (SMEs) of the economy (Jadwa, 2017). Banks are, however, still finding it difficult to provide credit for small businesses that meet Basel's capital requirements. Most of the current credit-risk models only apply to large corporations with little constructed for SMEs applications (Altman and Sabato, 2007). This study fills this gap by focusing on the Saudi SMEs perspective.

My empirical work constructs a bankruptcy prediction model based on logistic regressions that cover 14,727 firm-year observations for an 11-year period between 2001 and 2011. I use the first eight years data (2001-2008) to build the model and use it to predict the last three years (2009-2011) of the sample, i.e. conducting an out-of-sample test. This approach yields a highly accurate model with great prediction power, though the results are partially influenced by the external economic and geopolitical volatilities that took place during the period of 2009-2010 (the world financial crisis).

To avoid making predictions in such a volatile period, I rebuild the model based on 2003-2010 data, and use it to predict the default events for 2011. The new model is highly consistent and accurate. My model suggests that, from an academic perspective, some key quantitative variables, such as gross profit margin, days inventory, revenues, days payable and age of the entity, have a significant power in predicting the default probability of an entity. I further price the risks of the SMEs by using a credit-risk pricing model similar to Bauer and Agarwal (2014), which enables us to determine the risk-return tradeoffs on Saudi's SMEs.

***Key words**: Saudi Vision 2030, Banks, SMEs, Credit Risk, and Pricing Credit Risk*

ACKNOWLEDGMENTS

I would like to express my appreciation to my doctoral supervisor, Professor Huainan Zhao, then at the Cranfield School of Management (SOM) and now at Loughborough University. He has provided me with great support throughout the journey. He has always inspired and encouraged me to write a doctoral thesis with the highest quality, which makes significant contributions to both practical and academic world.

I also appreciate the advices and support given by my doctoral panel members: Dr. Vineet Agarwal (co-supervisor) and Dr. Andrea Moro. They have been of great value to me throughout our panel meetings. I thank Professor Emma Parry and many faculty members at Cranfield SOM.

I am also grateful to a number of practitioners outside Cranfield SOM for their supports and comments, such as Turki Alhamdan and Guahn Ramakumar at Samba Financial Group; Khaled AlGwaiz, CEO at ACWA Power Holding; Tirad Mahmoud, CEO at Abu Dhabi Islamic Bank; Sajjad Razvi, ex-CEO at Samba Financial Group; Osama Al-Mubarak, Head of Kafalah Program; Mohamed Al-Kuwaiz, Vice Chairman of Capital Market Authority; and many others who have provided testimonials and comments throughout my research journey.

Many thanks also to Abdulaziz Al-Hulaisi, the CEO and Masood Zafar, the Group CRO, at Gulf International Bank, Bahrain, who provided me with the support to complete my research.

Last but not least, I am very grateful to my family who supported and encouraged me throughout my research journey. I dedicate this thesis to my family and my country.

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LIST OF ABBREVIATIONS

AUC	Area Under the Curve
BCBS	Basel Committee on Bank Supervision
CMA	Capital Market Authority
COGS	Cost of Goods Sold
CSOM	Cranfield School of Management
DA	Discriminant Analysis
DBA	Doctorate in Business Administration
DF	Defaulted Firms
DSCR	Debt Service Coverage Ratio
EAD	Exposure At Default
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
FASB	Financial Accounting Standards Board
GCC	Gulf Cooperation Council
ICIEC	Insurance of Investment & Export Credit
IFC	International Finance Corporation
IFC	International Finance Corporation
IFRS	International Financial Accounting Reporting Standards
IID	Identically Distributed Errors
IIF	Institute of International Finance
K.S.A	Kingdom of Saudi Arabia
kNN	k-Nearest Neighbour Algorithm
LGD	Loss Given Default
LGS	Loan Guarantee Schemes
ln	Natural Logarithm
M&As	Mergers and Acquisitions
MDA	Multiple Discriminant Analytic
MDA	Multiple Discriminant Analysis
Mil	Million
MoF	Ministry of Finance
NCB	National Commercial Bank
ND	Non Defaulted Firms
NFIB	National Federation of Independent Business
NN	Neural Networks
NPLs	Non-Performing Loans
OECD	Organization for Economic Co-operation and Development (OECD)
PCA	Principal Component Analysis
PDs	Probability of Defaults
RAROC	Risk Adjusted Return on Capital
ROA	Return On Assets
ROC	Receiver Operating Characteristics
ROC	Receiver Operating Characteristic
RPA	Recursive Partitioning Algorithm

SAMA	Saudi Arabian Monetary Agency
SBA	Small Business Administration
SBCS	Small Business Credit Scoring
SIDF	Saudi Industrial Fund
SIMAH	Saudi Credit Bureau
SMEA	Small and Medium Size Enterprises Agency
SMEs	Small and Medium Enterprises
SVM	Support Vector Machine
U.K.	United Kingdom
U.N.	United Nations
U.S.	United States
VaR	Value at Risk

1. FOUNDATION

1.1 Introduction

There have been ongoing interests in evaluating credit risk for Small and Medium Enterprises (SMEs). Academic and practical studies, including studies from the Organization for Economic Cooperation and Development (OECD) and the United Nations (U.N.), have been encouraging nations to overcome the challenges facing lenders in dealing with small businesses by promoting financial innovations. Berger and Udell (2006) publish one of the most compelling discussions of the environment surrounding small business lending, which concerns factors that include lending technologies, financial institutions structure and lending infrastructure. Government supported programs have also been a major driver of small business credit lending. One of the Saudi 2030 Vision's primary goals is to use the specialized fund vehicles such as the Kafalah (2017) program to support Saudi SMEs. Many of the financial innovations, discussed in the literature review of this study, have paved the way for the lending uptick in the small businesses segment, which is being viewed as a hybrid of corporate and retail lending approaches (Dietsch and Petey, 2004). Such approaches have derived statistical-based credit risk models, which forecast a firm's default risk and assign credit ratings to SMEs, the most commonly used approaches for SMEs lending.

1.2 Statement of Problem

Small businesses are an important topic in today's economy for a variety of reasons. Financial Institutions have become increasingly interested in extending credit to small businesses due to the growth and return potential in this business segment. In corporate banking, large companies receive the required attention from banks because they are a matured segment with a clear track record and a low probability of default. This is not the case in the SME segment whose credit needs are, thus, not met. Small businesses are perceived as volatile because of low capital, small asset bases and lack of financial transparency (Haron and Shanmugam, 1994; Keasey and Watson, 1994). Credit officers also view small business lending as unworthy because of the time and effort they must spend compared to the anticipated profits. This means that it is difficult to manage SME portfolios because they require economies of scale, which take time to achieve (United Nations, 2001). Consequently, most SMEs depend on self-funding.

Many international banks have designed credit-risk models for large caps, while only a few banks have designed credit-risk models for SMEs. In Saudi Arabia, this has also been the case because SMEs credit-risk assessment is still considered a grey area that is difficult to manage. SMEs credit-risk modelling is essential for assessing risk in all aspects of a business and being able to set pricing for various risk levels (Altman and Sabato, 2007).

It is important to model the credit risk of SMEs in order to mitigate unexpected risk events. Credit risk assessments predict the event in which borrowers default on their loan payments. Banks try to calculate the probability of defaults by borrowers. Credit risk management involves quantifying the probability of default. In this study, I review the literature on the credit risk models in order to develop a model for measuring the credit risk for Saudi SMEs.

During my tenure as an executive bank officer for over seventeen years, I witnessed a decline in SMEs cases by the bank's credit committee. This led me to realize that these small business entities require a simpler but stronger format for borrowing in order to support their business ambitions. Based on the literature, most credit-risk models apply to large corporations while a limited portion apply to SMEs (Altman and Sabato, 2007). Yet there is great potential for financial institutions to generate a higher return on assets (ROA) by offering credit facilities to these small business entities. This study fills a gap in the literature by designing a credit-risk model devoted to Saudi SMEs.

In many parts of the world, including Saudi Arabia and other Gulf Cooperation Council (GCC) countries, many financial institutions have attempted to explore the arena of small business credit. However, it is still unclear how to approach small business credit, leaving many questions unanswered, such as how lenders assess small business credit and what credit risk models and pricing they should apply in order to grow the SMEs portfolios and make them profitable.

1.3 Significance of the Study

Although this research has a focus on Saudi Arabia, given that there is a clear issue with respect to financing small businesses in this country, it can also be applied to many other countries because the issue of small business lending is a global challenge. One of the Saudi 2030 Vision's primary objectives is to promote SMEs access to credit (Jadwa, 2017).

Academically, this study aims to make several contributions. First, it constructs a model, in line with Altman and Sabato (2007), which is based on logistic regression method to predict default. The model includes key quantitative and qualitative variables of significance for the Saudi SMEs' sample portfolios, which are different from most studies employing the U.S. and U.K. data. Second, this is the first study to develop a default prediction model (or bankruptcy model) for Saudi SMEs. In terms of practical contributions, this can be very useful for measuring the credit risk of SMEs in GCC countries and other emerging markets. The Financial institutions, with their SMEs clients' data sets, can further enhance and create internal credit-risk models by following the steps outlined in this research. With good credit-risk models, the risk management of the whole financial system can be improved and lenders can resort to more accurate pricing of risk. As a sign of practical contribution, this study can be used by the Saudi Arabian Monetary Agency (SAMA) and Small and Medium Size Enterprises Agency (SMEA) in conjunction with Quaiem services (Ministry of Commerce and Investment, 2016)[1].

Another goal of this study is to offer practical contributions to financial institutions with regards to unexplored areas of due diligence. These practical tools could improve their ability to approve credit to eligible small business entities, which would ensure higher returns coupled with minimal losses. Having a robust credit risk model for SMEs application would help banks to meet Basel accord[2] requirements for capital adequacy (Altman, 2001).

1.4 Structure of the Study

The remainder of the thesis is structured as follows: chapter two provides a background for SMEs lending literature; chapter three positions the study within the literature on credit default, rating and risk; chapter four provides brief data descriptions including basic statistics; chapter five outlines the methodologies undertaken in the research; chapter six presents and discusses the research results and findings; chapter seven concludes the research; and finally, the thesis ends with an impact assessment.

[1] Quaem is one of the Saudi Ministry of Commerce and Investment projects to collect and statistically analyze the audit annual financial statements of all companies licensed to work in Saudi Arabia. I am involved in a project that is coordinated between SAMA and SMEA in order to promote funding access to Saudi SMEs as part of Saudi 2030 Vision.

[2] Basel Accords, including Basel I, II and III, are set by the Basel Committee on Bank Supervision (BCBS), which provides recommendations on banking regulations regarding liquidity, capital, credit, market risk and operational risk (see bis.org).

2. BACKGROUND AND GENERAL LITERATURE REVIEW

First, it is important to properly define small business and differentiate it from medium business or medium enterprises. It is also crucial to review the importance of small business as it is the subject and main driver for this study. There are many challenges facing lenders when analysing the small business segment. In light of these challenges, I review the credit environment, including lending approaches and trends financial institution experts follow and financial institution structure and the lending infrastructure.

In the next chapter, I define credit risk and credit default. After that, I review the literature of modelling small business credit in order to develop the right credit portfolio that has a good balance between default risk and expected return.

2.1. Small Business: Definition

The definitions of small business differ across the globe. Most public and private institutions agree to choose annual revenues or sales generated by an entity in defining small businesses. Some uncommon definitions take into consideration the number of staff an entity has while other definitions consider the balance sheet size. Table 1 presents some international definitions for small businesses as quoted by international public institutions:

Table 1. SME definitions by international institutions

Institution	Maximum # of Employees	Max. Revenues or Turnover ($)	Maximum Assets ($)
World Bank	300	15,000,000	15,000,000
MIF – IADB	100	3,000,000	(none)
African Development Bank	50	(none)	(none)
UNDP	200	(none)	(none)

Source: Gibson and van der Vaart, 2008

The Saudi SMEs Program for guaranteeing SME exposure to banks, Kafalah (Arabic word for guarantee), defines SMEs as those entities with annual turnover or sales up to SR 30 million (equivalent to US$ 8 million) (Kafalah, 2017).

The newly established Small and Medium Enterprise Authority has decided to define SMEs based on the number of staff or the annual turnover as follows (Ministry of Commerce and Investment in Saudi Arabia, 2016):

- Micro entities are those entities that have less than or equal to 5 full time staff members, or has annual turnover of up to Saudi Riyals 3 million[3].
- Small size entities are those with 6-49 full time staff members, or annual turnover between Saudi Riyals 3-40 million.
- Medium size entities are those with 50-249 full time staff members, or annual turnover between Saudi Riyals 4- 200 million.
- Large size entities are those entities with more than 250 full time staff members, or annual turnover that exceeds Saudi Riyals 200 million.

In case the annual turnover of the entity is not available, then the classification criteria will be the number of full-time employees (Ministry of Commerce and Investment in Saudi Arabia, 2016).

[3] 1 US Dollar = Saudi Riyals 3.75.

Small businesses are a major contributor to the economy and are a source of employment. The labour market for SMEs is less affected than the labour market for large companies during difficult periods such as economic recessions. Varum and Rocha's (2013) study on Portuguese firms during the period between 1988-2007 validates this claim concluding that small businesses are important for the growth of the economy. They serve as stabilizers for the economy during unstable periods, a point that is at least valid within the European Union community (Varum and Rocha, 2013). Large companies are dependent on small businesses for their supply needs because they cannot produce and generate everything.

In the United States, SMEs are considered to be the major contributor to the country's employment. The number of published patents for small businesses is higher than for large companies, emphasizing small businesses as major contributors to innovation and technology. Government regulations are moving away from an industrial framework to a new framework geared towards promoting SMEs. This framework focuses on employment growth, information transfer and innovation (Audretsch, 2002) and is based on experience and research studies.

Small businesses contribute more to the economies of developed countries than to those of developing countries. This suggests reliance by large economies on SMEs. Despite the fact that large firms form most of the activities in developed economies, SMEs employ most of the labour force. Moreover, most of the new products and new inventions come from the small business sector (Beck and Demirguc-Kunt, 2006). These studies emphasize the importance of small businesses and additional studies in the literature further confirm that small businesses are considered strategic drivers for the growth of any economy. The importance of small businesses is not only limited to financial results but also social impact. Having discussed the importance of SMEs, the next section covers the challenges facing lenders when dealing with SMEs.

2.2. Three Challenges Facing Lenders When Dealing with Small Businesses

First, there are challenges associated with the unavailability of borrower's information. When analysing borrowers' credit information, lenders often look at what is called the 5 Cs of credit, or the five credit factors; Capacity, Collateral, Character, Capital and Conditions. Credit capacity defines the credit facility's terms, which must be consistent with the borrower's ability to repay. Collateral ensures that the value and the marketability of the collateral (property, inventory, receivables, or any type of fixed asset) are acceptable.

Character is defined by the borrower's ability to demonstrate integrity, honesty and financial stability. Haron and Shanmugam's (1994) 5Cs study in Malaysia involving five banks and 49 credit officers concludes that the character of the client was the most important factor and challenge for lenders when underwriting small business credit applications. The issue of character involves observations pertaining to proper professional management, corporate governance, financial planning and track record (Haron and Shanmugam, 1994).

Small businesses are generally perceived as volatile due to low capital and small asset bases. The lack of financial transparency and ability to produce financial statements form a huge challenge for creditors. Credit officers are unable to make credit judgment due to lack of quality information. SMEs tend to dishonour their contractual commitments: small business owners are not accustomed to legal contracts pertaining to the fund borrowing process. Most loan agreements include legal and financial clauses that are imposed on the borrower and because of little experience, small businesses tend to violate some of these legal clauses and/or financial covenants (Keasey and Watson, 1994).

Second, lending to small businesses is perceived as challenging due to factors associated with macro-economic conditions such as high interest rates, high unemployment rates and owners' tendencies to exit the business during difficult times. This is clear because of low absorbing capacity as a result of low capital. Small businesses unlike large firms, generally do not have a bailout plan should things fail to proceed as predicted (Everett and Watson, 1998). Moreover, research suggests that if the lending entities are not developed enough from micro and macro perspectives, their loan officers will find it difficult and challenging to lend to small businesses. This is evidenced by the fact that lending improves in countries with better conditions with regards to the SME lending sector. Lending in general requires an appropriate environment ensuring smooth transactions between lenders and borrowers. These include but are not limited to legal conditions, economic conditions and availability of borrowers' credit information (Beck and Demirguc-Kunt, 2006).

Third, credit officers view small business lending as not worthy because of the time and effort required in comparison to the anticipated profits from the transaction. This emphasizes the difficulty in managing SME portfolios as it requires economies of scale, a process that takes time to achieve (United Nations, 2001).

The Organization for Economic Co-operation and Development (OECD)'s (2004) study for financing SMEs and entrepreneurs, conducted in 32 nations, indicates that the process of financing small businesses continues to encounter the credit crunch as a result of banks' reduced debt appetite post-financial crisis ignoring the monetary easing. The resulting credit delinquencies after the crisis have made it more difficult to expand credit to small businesses. Both lenders and investors are careful when it comes to small business consideration. Nevertheless, governments are continuing to extend and encourage support for small businesses as they believe SMEs should be the growth engine for the future (Organization for Economic Co-operation and Development, 2004). Table 2 presents these challenges.

Table 2. Challenges in access to finance and recent financial innovations

SME Constraints in Access to Finance	Banks' Response to Constraints of Access
SMEs are regarded by creditors and investors as high-risk borrowers due to insufficient assets and low capitalization, vulnerability to market fluctuations and high mortality rates.	Reducing information asymmetry of SMEs and high perceived risks by using credit scoring systems, external information providers, risk self-assessment for the SME entrepreneurs, pricing to the level of risk; sharing risk with third parties (loan guarantees) using covenants as an alternative to loan guarantees and setting up special support units for high risk customers such as start-ups.
Information asymmetry arising from SMEs' lack of accounting records, inadequate financial statements or business plans makes it difficult for creditors and investors to assess the creditworthiness of potential SME proposals.	Reducing costs of lending by applying latest information technologies; streamlining the organization and simplifying the lending process.
High administrative/transaction costs of lending or investing small amounts do not make SME financing a profitable business.	Developing products better adapted to SME needs.
	Improving financial services for SMEs through training of bank staff and the segmentation of SME customers.
	Cooperating with SME organizations and other business development providers in order to reduce risks and costs and combine financial with non-financial services.

Sources: Organization for Economic Co-operation and Development, 2004 and United Nations, 2001

2.3. Small Business Credit Environment

It is important to address the environment for small business lending in order to look at the different approaches available for lenders. These form the basis for credit officers when they assess the credit risk of SMEs. Credit officers work within financial institutions that have different structures within the country and across the globe. The literature suggests that the small business environment has key components, defined in this chapter, in which the business can operate. Figure 1 describes this credit environment based on the literature domain.

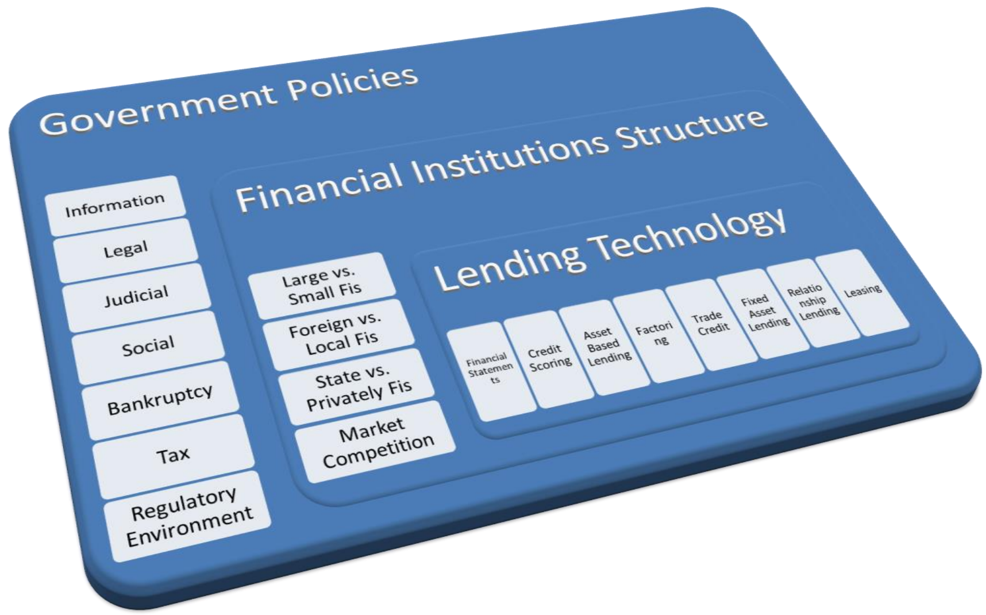


Figure 1: Availability of credit to SMEs environment

Source: Berger and Udell (2006)

2.3.1 Lending technologies

Lending technologies can be defined as available lending approaches for credit officers that help in making credit decisions. These technologies can be products, processes, or techniques. The implementation of these technical approaches is not consistent for all borrowers. Each transaction may require a different technical approach that might not be applicable in other transactions. Some examples of these lending techniques are discussed below.

Financial statements lending*:* This is the process of looking at the balance sheet, income statements, cash flow statements and financial ratios of the borrower. Most lenders prefer to look at audited statements rated by firms. Nevertheless, most small businesses lack the experience of producing reliable financial statements. The main objective of lenders when looking at financial statements is to assess the borrower's capacity to pay back the loan based on historical track record. Financial statements lending includes looking at different financial ratios such as the liquidity ratios and leverage ratios. Financial statements lending is considered sophisticated and requires accounting and financial expertise. It usually takes time and requires intellectual experience. It is considered costly and in most cases not feasible for small business lending due to the time and effort required by the underwriters (Uchida, 2011).

Small business credit scoring: This is the technological financial model that generates credit scores that are used for making loan decisions. It depends on inputting consumer and SME related information. Credit scoring has made small business lending very efficient, as credit officers do not have to meet with borrowers when it comes to making credit decisions. Behavioural credit scoring is a credit scoring model that analyses financial information over time (Sohn and Kim, 2013). Credit scoring is determined by internal rating systems. One of the outputs for these models is the risk group, which can serve as the basis for credit assessment. Another output is the probability of default across obligors which can produce standardization across the assessment of portfolio (Zelgalve & Romānova, 2009).

Probability of defaults (PDs) can be considered as a risk rating (Pederzoli et al., 2013). Credit scoring has a direct relationship with quantity, price and risk of small business credit and can be widely used. Credit scoring is also useful in reducing the operational costs of lending or can be combined with other lending processes (Berger, Frame and Miller, 2005). In a German and French SME study, Dietsch and Petey (2004) recommends segmenting the SMEs by size (very small, small and large) making the lending decision more appropriate to the small business segment (Dietsch and Petey, 2004). Melo (2014) comments on the advantage of credit scoring: “there is an awkward ‘catch-22,’ credit grantors will be able to expand access to SME credit in a sustainable way only if they can reduce the time and cost involved in current originations processes, which cannot be justified for smaller amounts of credit” (Melo, 2014).

Another advantage of the risk rating models that generate credit scoring is their ability to generate global risk ratings using the individual risk ratings generated from the internal risk model as demonstrated in a study on French Banks (Dietsch and Petey, 2002). The model is good for small credits up to US$ 100,000-250,000 and that are high risk coupled with high pricing. Besides its use in small business financing, credit scoring was originally introduced in individual lending such as credit cards. Unfortunately, credit scoring is not always accurate since the detailed interaction between lenders and borrowers is almost eliminated. In general, credit scoring is a good approach for mass lending. My research focused on this type of lending which involves modeling the credit risk of SMEs in Saudi Arabia.

Assets based lending: This is lending based on the specific entity’s assets such as stock or accounts receivables, which serve as collateral for lending. It is normally used for working capital financing. This type of lending depends on liquidation of the collateral as the primary source of payment unlike other lending types where the asset is used as a second source of payment. Asset based lending looks for particular assets to ensure that the money lent is not diverted to other uses. However, it is difficult to track money in some transactions when ensuring that the borrowed money is being specifically spent on the particular asset since the borrower may have several assets and thus uses for the money (Krasowskik, 2015).

Factoring: This is the process of selling an entity's accounts receivables to a lender or a factor. Factoring deals with receivables only. The process involves transferring the ownership of receivables from the borrower to the lender. The collection of receivables in most cases are kept with the borrower (the seller) based on agency agreement against agreed upon fees. Additionally, in most cases the sellers of these accounts receivables charge a premium when they factor in the portfolio. Factoring is good in developed countries where credit information about clients is available through credit agencies. Another alternative approach for SMEs is "Reverse Factoring," where receivables of only quality clients are sold or factored, in light of lack of credit information (Montibeller et al., 2007). Factoring is becoming popular with SMEs, however it is considered expensive since the seller passes most of their anticipated profit on these receivables to the buyer.

Fixed assets lending: This process involves lending against fixed assets that have a long economic life (more than one year). The assets can be property, land, warehouse, office, vehicles or machinery. The process depends on pledging the fixed asset in favor of the lender, which is then used as collateral. The fixed asset usually has a public registration. The lender usually sells the collateral if the borrower fails to repay back the loan. The process involves a contract and facility to value ratio, which is usually less than 100%. The fixed asset is used as a second way out if the cash flow of the borrower is not enough to repay the facility. The contract has an amortizing repayment schedule and financial conditions. Collateral increases the local lender appetite for credit and forms as an incentive for financing. Collateral makes lenders more comfortable with the client as they ensure that the customer's commitment is added to the transaction (Inderst and Mueller, 2007). Lenders usually ask for collateral when the relationship with the borrower is not long and this has been mostly in new credit relationships (Voordeckers and Steijvers, 2006).

Relationship lending: This is the process of lending using non-financial information such as the soundness of the borrower in the market and the performance track record based on information gathered locally from clients, suppliers, competitors, etc. Relationship lending is very difficult to implement as it does not use solid information (Berger and Udell, 2006).

Previous studies suggest that small banks tend to use relationship lending more than large banks because of proximity to clients. However, some studies suggest that the size of the bank does not matter with respect to relationship lending when it comes to small business financing (de la Torre et al., 2010). The relationship length of small businesses and banks determined the credit appetite by banks in Finland, suggesting that more weight is placed on time and hence relationship (Fredriksson and Moro, 2014).

Moro and Fink (2013) argue that German and Italian banks' credit officers' trust on small business owners and managers forms the basis for credit appetite, which is one aspect of relationship lending (Moro and Fink, 2013). Relationship lending increases the probability of providing future products to clients as compared to lenders who do not enjoy relationships with small businesses (Bharath et al., 2007). Relationship lending is more important than other factors such as demographics when it comes to lending and offering pricing packages (Neuberger and Räthke-Döppner, 2015).

Trade credit: This refers to the credit process that is extended by non-bank institutions such as suppliers or sellers. It can involve financial statement analysis, credit scoring, relationship seasoning or a combination of these. This process is usually conducted in less developed economies where there is a lack of bank products that can support SME lending. Small businesses widely use trade credit due to the credit constraints they face (Danielson and Scott, 2004).

Leasing: This is the process of selling assets to a lender and then leasing back of the assets by the borrower. The assets can be real estate, equipment, or a vehicle and is also used as collateral until the debt is paid off, serving as a second way out after the cash flow of the company. Studies show that small firms use less of these types of financing (Beck, Demirgüç-Kunt and V.M., 2008). Just like fixed asset lending, leasing requires leasing contracts that specify the facility to value and the credit conditions. Leasing contracts in most cases end up with the transfer of the fixed asset from the lender's ownership to the borrower. In most leasing contracts, lenders ask for life and asset insurance to mitigate the succession risk that can potentially develop from the transaction (Beck and Demirguc-Kunt, 2006).

2.3.2. Financial structure of institutions

The structure of financial institutions in the lending environment can make a difference. Large financial institutions often gain from the economies of scale compared to small institutions because of the higher lending capacities provided by their wide geographic infrastructure. Small institutions tend to focus more on lending to small businesses more than large institutions because of their size and tendency to use the relationship lending approach (Moro and Fink, 2013).

Moreover, locally owned institutions might do better in relationship lending compared to foreign-owned institutions due to their local market knowledge and familiarity. State owned institutions usually do not do well in relationship lending compared to privately owned companies because privately owned companies are more selective and more risk averse to SMEs compared to government owned institutions. This can explain why government owned institutions, while large in nature, often support the credit provided to small businesses due to government mandates. Market competition also plays a major role in small business lending. Financial institutions with great power and liquidity can dictate pricing and appetite toward lending (Berger and Udell, 2006).

Based on studies, the decentralized organizational structures of banks are more responsive to the needs of small businesses because they involve branching at city and regional levels. The branch managers are usually closer to clients compared to credit managers of centralized banks. They are also in a better position to assess risk and avoid possible ambiguity as a result of close customer interface (Canales and Nanda, 2012). Studies also revealed that the Mergers and Acquisitions (M&As) across banks can reduce the credit to small businesses as M&As create large banks that tend to lend more to large clients. As a result, small banks are lending more to small businesses. Furthermore, studies in the U.S. suggest that increasing chances for banks to expand in more states helps small businesses get financing; however, it does not necessarily increase the amount of credit (Rice and Strahan, 2010). Further studies indicate that the equity held by top management in SMEs improve performance and hence accessibility to credit market (Zahra, Neubaum and Naldi, 2007).

2.3.3 The lending infrastructure

The information environment includes the quality of financial statements, which depends on external auditors producing financial statements. It is also essential for monitoring financial covenants and ratios. Additional examples are financial indices and consumer and commercial credit bureaus. The legal, judicial and bankruptcy environments determine the lenders confidence in the environment and can often have effects over small businesses lending. The social environment has direct impact over lending infrastructure. Examples of social environment practices are trust, business language and relationship lending. Finally, the tax and regulatory environments play a major role in lending to small businesses. Regulatory decisions and tax issues are examples of lending infrastructures (Berger and Udell, 2006).

Experience also matters as part of the infrastructure and decision making process. Anderson (2004) finds that different experience levels across the sample made different lending decisions. This study covers 19 business students, 19 junior credit officers and 23 senior credit officers. Not surprisingly, they all reached different credit decisions. The senior group asked for the most detailed questions before making a credit decision, meaning experience makes a big difference. Decisions were also different across the sample at different experience levels.

2.4. Small Businesses and Government Sponsored Programs

Government programs such as Small Business Administration (SBA) in the U.S. have been a good example in giving small businesses access to the capital market. Nevertheless, studies argue that SBAs do not correct the small business credit failure. Such programs are devoted more to higher risk clients (Haynes, 1996). In some countries, government support is in the form of Loan Guarantee Schemes (LGS) that help small businesses obtain financing from the market. Government has economic and social goals associated with those guarantees which cost the government as the guarantees have premiums that need to be paid and issued in the form of a percentage of the value of these guarantees (Kuo, Chen and Sung, 2011). Regulators including central banks have impact over small businesses. Beck, Demirgüç-Kunt and Maksimovic's (2005) study on 54 countries suggests that financial, legal and corruption issues make it difficult for small businesses to obtain financing.

In Saudi Arabia, the two major public programs devoted to small businesses are 1) Kafalah which is sponsored by the Saudi Industrial Fund (SIDF) and provides assistance in the form of financial guarantees for participating financial institutions and 2) the small business program sponsored by the Saudi Savings Bank where assistance is provided in the form of free rate social loans. Privately owned banks conduct business separately from the two Saudi government sponsored programs. Some local banks try to work with international public programs facilitated by for example, Islamic Corp. for the Insurance of Investment & Export Credit (ICIEC) signing a memorandum of understanding with the National Commercial Bank (ICIEC, 2012).

A study conducted on 129 countries concluded that, improvement in lenders' rights and regulation of information exchange can improve the credit appetite and the credit supply for small businesses (Djankov, McLiesh and Shleifer, 2007). In countries where the legal system is weak with no protection for lenders' rights, lenders tend to share the risk of lending to small businesses with multiple banks in order to reduce the undertaken risk (Hernández-Cánovas and Koëter-Kant, 2010).

2.5. Trends in Small Business Credit Management

The process of lending to small businesses is evolving with lenders always trying to find the right approach in handling the credit risk of small businesses, whether through applied technology or organizational structure. This study discusses the different lending technologies and the circumstances in which these lending technologies can be used. A Polish study observed that there are many differences with respect to the way small business credit risk is handled within the commercial banking sector, suggesting that every case has its own merit (Frakins, 2004).

Small business lending has made good progress in developed countries. Both lenders and borrowers are benefiting, which in turn benefits the economy. In fact small business financing is becoming a profitable business. There are trends and approaches in the U.S. and Europe that aim to make small business financing successful. Some of these trends and approaches have already been covered in the literature review and include small business credit scoring models and the use of different financial technology instruments. This involves the use of information from outsourced parties, getting self-evaluation from the small business owners and diversifying the risk of small business lending with other banks through the multibank lending approach.

Moreover, banks use loan covenants to establish guidelines for SMEs. Banks also provide training for the owners and managers of small businesses to ensure better performance and to increase awareness in the community. Other trends include efforts to reduce transaction costs by offering the right product and technology to the customer, tailored to his/her credit needs. Banks also provide proper coaching for their junior officers on how to handle the credit of small businesses through specialized credit and financial analysis programs. They also segment the business based on size. Some financers seek support from public institutions in order to reduce risk by getting guarantees for these exposures (United Nations, 2001).

The literature cites several examples of how SME lending is handled; however, this study focuses on the most relevant examples to Saudi Arabia, given that countries are different in terms of economy, culture, demographics, etc.

Kaya and Alpkan (2012) suggest in their study on SMEs in Turkey that SME owners should seek assistance from consulting firms for business directions, to ensure achieving better results. The study also suggests that SMEs should hire capable finance managers to help resolve the information reporting issue. Furthermore, it recommends that staff in SMEs should be trained to do professional jobs, rather than hiring professionals, in order to reduce the cost of attracting professionals (Kaya and Alpkan, 2012).

Another study performed on SMEs in 76 countries reveals that the SME credit market is associated with perfect credit information sharing and favourable investment environment (Dietsch and Petey, 2004). Salkić's (2013) study in Bosnia also reveals a similar result. Everett and Watson (1998) find in their study that it is advisable for regulators to make the required data gathering and direction in order to help the development of SMEs segment internationally.

Globally, the International Finance Corporation (IFC) has been trying to promote development and credit supply for small businesses by helping financial institutions in two main ways: a) developing the banking theology infrastructure, b) assisting Financial institutions in providing financing for small businesses through sharing international experiences. IFC recommends that Financial institutions follow the "mass customized approach" of using financial technologies that reduce transaction costs and increase profitability of Financial institutions by applying it on the maximum number of clients. It also involves investing in infrastructure and technology and providing the required training to grow the experience. IFC focuses on building the right capability to handle business through business plans and feasibility studies. It also includes monitoring progress and providing the right coaching (United Nations, 2001).

2.6. Small Business Credit Management Approach as a Hybrid of Corporate and Retail Lending Approaches

Credit Cards have been an important mode of financing for both consumers and small business owners. There is a clear relationship between credit card usage and small business financing (Dietsch and Petey, 2004). This is not a coincidence as small business lending might be described as a hybrid of corporate lending and retail lending. Danielson and Scott’s (2004) study in conjunction with the National Federation of Independent Business (NFIB) shows that the demand for credit card financing by small businesses increases heavily when small businesses face credit constraints. This is happening despite the high cost of financing and the fees charged for credit card usage. The NFIB study gives insight into my research by providing evidence for a relationship between credit cards and small business financing, although it does not articulate it from the suppliers’ or financers’ perspective (Danielson and Scott, 2004).

Additional evidence is the fact that small businesses are less sensitive to bank pricing and tend to accept high interest rates charged by lenders due to the limited availability of credit supply. Small businesses have limited credit sources and as a result of the minimum size requirement such as capital and revenue, access to bond and capital market is not applicable for SMEs. There is an inverse relationship between the cost of borrowing and the use of money and a positive one between the cost of fund and the federal funds. In general, small businesses benefit less from a change in cost of funds pricing, compared to large businesses (Walker, 2010).

The literature discuses small business pricing and in some cases calls it “price discrimination,” as pricing is high when it comes to small business financing compared to large firm financing. Price has a negative relationship with distance meaning the shorter the distance between the lender and the small business client, the lower the price charged by lenders and vice versa (Degryse & Ongena, 2005).

Furthermore, the small business lending approach is described as a relationship and tailormade lending approach. Carter and McNutly’s (2005) study concludes that holding all economic variables that might influence loan pricing constant allows small banks to perform better than large banks because small banks mostly deal with small business segments, given the higher return. This is in line with DeYoung, Hunter and Udell’s (2004) model. On the other hand, the same study found that large banks do better than small banks when it comes to standardized lending products such as retail credit cards, which depend on scoring models. According to the study this finding may lead large banks to apply the scoring model to small business lending and become completive (Carter and McNutly, 2005).

Robinson and Finley (2007) study the use of credit cards by owners of small businesses from the U.S. Census Bureau's 2001 Survey of Income and Program and found consistent results. The study surveyed sole proprietors of both incorporated and non-incorporated businesses and concluded that sole proprietors are the major users of credit card debt, further establishing the relationship between small businesses and credit card usage.

Controversially, the use of credit cards by business owners as a means of financing in light of the shortage in availability of credit for small business, led banks to change notices of use, increase charges and reduce credit cards limits. This action by banks towards small business owners might increase the already foreseen difficulties in small business financing and might contribute to slowing down the economy and employment created by small business segment (Lahm Jr. et al., 2011).

Small business lending can be made in low amounts similar to credit card loans through scoring mode. Small Business Credit Scoring (SBCS) can work well for financing amounts less than $100,000, combining higher quantities and higher average pricing (Berger et al., 2005).

Extracting from Dietsch and Petey's (2004) article, "Should SME exposures be treated as retail or corporate exposures? A comparative analysis of default probabilities and asset correlations in French and German SMEs," the study used a one-factor credit risk model to provide new estimates of stationary default probabilities and asset correlations in the two samples. Not surprisingly, the study found that SMEs are riskier than large businesses with weak asset correlations (1–3% on average). On average, the relationship between the probability of defaults (PDs) and asset correlations is positive. The study concluded that "It is also possible to distinguish different segments inside the SMEs' population, at least between very small and small SMEs and large SMEs" (Dietsch and Petey, 2004).

2.7. Overview of Small Business Credit in Saudi Arabia

2.7.1. Saudi Arabia 2030 Vision and commitment to promoting SMEs

Saudi Arabia is a member of the G20 economies of the world and is one of the largest oil producers in the world. Its economy has benefited from high oil prices for the past decade, accumulating high monetary reserves. It has also experienced continuous budget surplus and was able to build foreign wealth.

King Salman said, “My first objective for our country is to be a pioneering and successful global model of excellence, on all fronts and I will work with you to achieve that…” The Kingdom of Saudi Arabia announced its 2030 vision (Table 3) to the world in 2016. According to the Crown Prince who is responsible for implementing the vision as the Chairman of the Council of Economic and Development Affairs, the 2030 vision is based on three pillars: 1) Saudi Arabia to be the heart of the Arab and Islamic worlds; 2) the kingdom to become an investment powerhouse; and 3) the country to be the hub connecting the three continents (Kingdom of Saudi Arabia, 2017).

Table 3. Goals of the Saudi 2030 Vision

Theme	Goals	Today	2030
A Thriving Economy	Private sector contribution (% of GDP)	40.0	65.0
	Logistic Performance Index (Rank)	49	25
	Non-oil exports (% of non-oil GDP)	16.0	50.0
	Public Investment Fund assets (SR billion)	600	7,000
	Global Competitiveness Index (Rank)	25	10
	Annual FDI inflows (% of GDP)	3.8	5.7
	Domestic output of the oil & gas sector (% of total)	40.0	75.0
	The Kingdom's GDP size (Rank)	19th	Top 15
	Saudi unemployment rate (% of Saudi labor force)	11.6	7.0
	Female labor force participation rate (% of working age females)	22.0	30.0
	SME output (% of total GDP)	20.0	35.0
A Vibrant Society	Number of globally recognized Saudi cities	0	3
	Social Capital Index (Rank)	26	10
	Average life expectancy (Years)	74	80
	Doubling the number of Saudi heritage sites registered with UNESCO	-	-
	Household spending on culture & entertainment (% of total)	2.9	6.0
	Individuals exercising at least once a week (% of total)	13.0	40.0
	Number of Umrah visitors per year (Million pilgrims)	8	30
An Ambitious Nation	Household savings (% of household income)	6.0	10.0
	Non-profit output (% of total GDP)	<1.0	5.0
	Number of volunteers per year	11,000	1 million
	Non-oil government revenues (SR billion)	163	1,000
	Government Effectiveness Index (Rank)	80	20
	E-Government Survey Index (Rank)	36	Top 5

Source: Jadwa, 2017

The Saudi 2030 vision puts an emphasis on Small and Medium enterprises (SMEs) as an important engine for growth and job creation. Based on the vision, SMEs today contribute only 20% to GDP. By 2030, the vision plans to increase SMEs' contributions to 35%. The Government is planning to remove regulation obstacles and established in 2016 the Small and Medium Size Authority, which aims to promote SMEs. One of the authority's first moves was the definition of SMEs based on annual turnover and number of staff. There will be incentives for financial institutions to increase lending to SMEs. The government is planning to increase SMEs' debt from financial institutions from 5% to 20%. Commitments to establish business incubators, specialized training institutions and venture capital funds are presented in the Vision to assist SMEs become a catalyst for economic growth. The Kingdom is committed to its vision and has devoted special emphasis to the SMEs sector (Table 4), seeing it as a rewarding opportunity (Jadwa, 2017).

Table 4. Commitments of the Saudi 2030 Vision

Goals		
Thriving Economy	Open for business	A developed digital infrastructure A flourishing retail sector A restructured King Abdullah Financial District
	Investing in the long-term	A renewable energy market A mining sector with full potential Localized defence industries
	Rewarding opportunities	A bigger role for SMEs An education that contributes to economic growth
	Leveraging its unique position	Building a unique regional logistical hub Integrating regionally and internationally Supporting our national companies
A Vibrant Society	With strong foundations	Corporatization: efficient and high quality healthcare
	With fulfilling lives	Irtiqaa: A more prominent role for families in the education of children Daem: meaningful entertainment for citizens
	With strong roots	The largest islamic museum The honor to serve Umrah visitors in the best way possible
An Ambitious Nation	Effectively governed	Qawaem: Increasing spending efficiency Effective E-government Shared services to government agencies King Salman program for human capital development
	Responsibly enabled	A more impactful non-profit sector

Source: Jadwa, 2017

2.7.2 Small business lending in Saudi Arabia

The shortage of lending to small businesses in Saudi Arabia is cause for worry in the banking community and the government. To combat this concern, the government is increasing support and subsidies to this business segment. Additionally, government is trying to establish a healthy lending environment for SMEs in order to contribute to the economy and local labour market. Lending in the SME sector is very low, at only 2% of the total debt size among lending institutions in Saudi Arabia. In a publication by the country's largest bank in terms of total assets, National Commercial Bank (NCB), the bank expects the small business sector to grow as a result of both Financial Institutions and government increasing exposure to the sector (Timewell, 2014). One of the most noticeable movements in Saudi Arabia is the improvement of the legal and court system, which can promote the development of the private sector and lender's appetite for SMEs (Chamoun, 2013). Small business lending in Saudi Arabia is contributing to the economy and based on NCB's annual publication, the total number of jobs created by SMEs in Saudi is projected to double from one million employment opportunities in 2010 to two million employment opportunities in 2015 (Timewell, 2014).

A study exploring strategies for SMEs in Saudi Arabia concluded that most business activities are part of the SME Sector and estimated that SMEs contribute 90% to the private sector and supplies more than 80% of employment (Saleh, 2012).

The Saudi government established a government-sponsored program in 2006 called Kafalah, managed by the Saudi Industrial Fund (SIDF) under the umbrella of the Ministry of Finance (MoF). The program aims to support small businesses that face difficulties in obtaining financing. The program works as a guarantor for small businesses when they obtain financing from participating Financial institutions and guarantees up to 80% of the provided financing. It is directed to those businesses that have key success factors but lack the capability to provide guarantees and the financial records required to get financing. The program has the following goals:

1. Help SMEs obtain Islamic financing in order to grow business and expand activities.
2. Encourage financial institutions to deal with small businesses.
3. Attract new customers segment to deal with financial institutions.
4. Develop the small business sector in order to contribute to the local economy.
5. Create new jobs by using minimum capital requirements.
6. Develop new Saudi cities that have low economic activities.
7. Provide training programs for the owners of small businesses.
8. Increase the awareness of owners of small businesses thorough seminars and business gatherings.

The program supports all business activities that contribute to the economy with the exception of the trading sector, which depends on goods and services imported from outside the country. The program's maximum lending amount per party/obligor is SR 2 million (equivalent to US$ 0.533.33 million). Table 5 shows the activities of the program since its inception (Kafalah, 2017):

Table 5. Accumulated number of Kafalah issued guarantees, value of guarantees and value of financing per business activity in 2016

Business Activity	Number of Entities	Number of Guarantees	Value of Guarantees in Saudi Riyals	Value of Financing in Saudi Riyals
Contracting, Construction	605	1,459	652,785	1,370,098
Trading	577	1,004	602,114	1,121,710
Manufacturing	172	284	192,156	373,043
Financial Service and Others	122	272	134,208	269,153
Tourism and Entertainment	115	180	115,271	186,651
Social Services	76	117	83,110	144,119
Transportation, Storage, Cooling	27	40	29,894	49,646
Utilities & Fuel	8	18	10,430	18,300
Mining and Oil	7	11	3,657	19,180
Agriculture, Fishing	2	5	4,164	5,500
Total	1,711	3,390	1,827,789	3,557,400

Source: Kafalah, 2017

3. LITERATURE REVIEW ON CREDIT RISK MODELLING

The literature on credit risk modelling and bankruptcy predictions is very rich as it spans many decades and uses varied credit risk models. Many authors have used these models as tools in multifarious ways. Most of these models are based on logistic regression, which is the same basis for this research, as is explained in the methodology chapter. I cover the credit risk models as they have evolved from the 1960s to the 2000s. Before going through the literature of the credit risk modelling and its types, it is important to define credit default, which is the dependent factor for any credit risk model.

3.1 Defining Credit Default

Basel II legislation, enacted in 2004, incorporates credit risk maintained by financial institutions to govern regulatory capital requirements. Based on Basel II[4] legislation, an entity can be considered defaulted if this entity is unlikely to meet its credit obligations to the financial institution or the lender after taking out the security provided by the entity (borrower). Alternatively, an entity or borrower can also be considered defaulted if past due amounts or obligations linger for more than 90 days. The bank account or the status of the obligor (lender) becomes non-accrual as the obligor is not able to meet his or her obligation toward the financial institution (Santos et al., 2007).

Based on Basel II definitions, it is important for financial institutions to measure the credit risk of borrowers in order to estimate the required capital requirements (Altman and Sabato, 2007). Measuring the risk can mainly be done in two different ways. It can be done externally by credit rating agencies for large corporates. Alternatively, banks can use internal rating models for non-externally rated entities. This approach is important

[4] Basel II is one of Basel Committee's banking regulations (Santos et al., 2007).

for banks in order to estimate the credit strength of non-externally rated entities. The development of such models falls within the subject of this literature review.

The second level of credit default definition, which refers to credit default in cases when the borrower is unable to meet the payment of the lender obligations for more than 90 days, depends on a bank assessment of the borrower's expected cash flow to pay the debt through debt restructuring. This relief can be temporary if the lender gives the borrower a second chance or restructures the exposure beyond the ninety days period (Santos et al., 2007). This relief depends on the business record of the borrower, its expected business performance and its ability to meet its loan obligation.

If the borrower's expected cash flow does not justify an exposure restructuring plan, then the lender has to assess the collateral. Moreover, the lender has to determine if the liquidation of the collateral can pay for the debt. In case the liquidation of collateral, or the second level (way out), can meet the payment of the obligation, then the bank can keep the exposure on accrual status. In some cases, there are third or fourth ways out in the form of legal guarantees against financially sound entities or individuals. The same approach applies when the bank has to assess all these way outs. On the other hand, if any of the ways out, including the collateral, falls short, then the bank has to put the exposure on non-accrual. Non-accrual status refers to the situation in which the lender has to stop accruing interest or profits on the exposure. In such cases, the credit exposures or loans become non-performing loans (NPLs) for which the bank has to consider provisioning options against the exposures (Gulf International Bank, 2016).

Given the above explanations for Basel II credit default, it is important to define the different terminologies associated with credit default. There are cases in which defaulted borrowers are called insolvent borrowers or bankrupted borrowers. Insolvency is a general term, which does not necessarily describe the borrower in the event of default. Insolvency refers to signs of credit default or weakness such as a drop-in-debt service coverage ratio (DSCR) below one. This offers clear evidence of the firm's inability to meet its current or short-term obligations. Insolvency can also refer to the entity's increase in leverage ratio (liabilities / equity) to an extent that clearly indicates the entity's inability to meet its obligation (Investopedia, 2016). There are other instances in which the current ratio (current assets / current liabilities) are less than one. Again, these can be temporary situations and do not necessarily indicate that the firms will definitely default in paying their obligations. In most cases, the lenders tend to restructure the debt so that the borrower can overcome the insolvency situation (Taffler, 1983).

On the other hand, bankruptcy is the event in which the firm goes into legal framework when the bank starts its claim process. In such framework, the lender can consider legal action such as invoking a promissory note or commercial papers written by the firm. In other cases, the company (borrower) seeks legal protection against its creditors through chapter 11 (Wu et al., 2010; Hillegeist et al., 2004). The most common term for the borrower's inability to meet a lender's obligations is credit default. Hence, all of these synonyms in the literature lead to the same meaning in the context of credit risk (Santos et al., 2007).

Credit is the most important type of risk as it is related directly to the borrower. In contrast, the other types of risks that are related to the bank involve operational risk, liquidity risk and market risks (Giesecke, 2012). Credit risk is the framework for studying and assessing the strength of the borrower by assigning a credit rating. Credit risk focuses on the purpose of the loan, whether it is for personal expenditure in case of individual borrowers, working capital spending for corporate borrowers, or capital expenditures related to contracts financing. Working capital financing is related to short-term spending, such as buying inventory for trading businesses or manufacturing. In some cases, working capital finance includes receivables financing due to delays in collecting credit sales. On the other hand, capital expenditures are related to long-term financing such as purchasing equipment/machines, moving assets, or building properties for the economic benefit of the firm.

Those are several purposes of financing. If the purpose is acceptable to the financer, it is important to study the several types of risks associated with the borrowers or the transaction. The several types of risk involve various delays in receivables collections due to market dynamics. Management risk is also important to consider due to the technical capabilities of running the day-to-day operations of a business (Gulf International Bank, 2016). Management has to enjoy a sound reputation with respect to know-how and integrity. The analysis of management risk involves the review of succession in order to ensure business continuity and avoid business disruption (Inderst and Mueller, 2007).

Credit risk management includes the mitigation of shareholders' succession risk and avoiding potential disputes among the shareholders. The risk of inventory or stock obsolesces[5] in the case of traders and manufacturers are important to consider and mitigate. A borrower has to make sure that fire hazards and the possibility of turnover inventory are insured in order to mitigate inventory risk. It is also important to extend facilities that do not exceed the requirements of the borrowers in order to avoid divergence of funds. Moreover, it is important to ensure that the assets of the borrower

[5] Stock obsolesces refers to a stock that is not valid for future use (Investopedia, 2016).

are large enough to conduct the business and generate the required sales to pay obligations.

Credit risk involves the analysis and mitigation of contractors' project status report. A projects status report includes the percentage of project completion, billed amounts and unbilled amounts. The labour adequacy, skills and compliance to labour law requirements are important aspects of credit risk management. There are other credit risk management elements that include visiting a borrower's premises, such as warehouses and facilities. Such visits are essential in order to make sure that the borrower is capable of performing its business (Berger et al., 2005). The availability of raw materials to manufacture goods is an important element to consider, as well. Clearly, having enough resources can mitigate the risk of business interruption and issues with suppliers and agencies. All of these factors have to be taken into consideration to mitigate the credit risk associated with borrowers' abilities to pay their debt (Kuo et al., 2011; Santos et al., 2007).

In finance, credit risk can be quantified by a credit rating. The mathematical equitation for estimating credit risk is:

Credit risk is the actual loss minus expected loss (where credit risk has to be higher than zero); where: Expected Loss = Probability of Default * Exposure at Default * Loss Give Default; where: Probability of Default refers to the probability of the borrower defaulting before the due date of meeting the obligations. Exposure at default refers to the actual obligations that are due excluding other exposures that are not due yet. There are cases in banking when exposure is divided on a certain schedule of payments in which only the due payment is considered for the calculation of the exposure at default (Behr and Guttler, 2007).

The loss given default (LGD) refers to the percentage of the exposure at default (EAD). The credit default risk can be mitigated, as mentioned earlier, by taking collateral against a loan as a second way out for exposure payments. In more developed markets for certain financial securities, banks tend to ensure exposures by buying the right credit defaults protections to hedge against credit deteriorations (Altman and Hotchkiss, 2011; Altman et al., 2005; DeYoung et al., 2004).

Studying credit risk and the possibility of mitigating it is important for banks as they comply with Basel II requirements. It is important for banks and financial institutions to determine the risk rating of its portfolios. Large corporations tend to enjoy an external rating by major credit agencies (Featherstone, Roessler and Barry, 2006). On the other hand, most SMEs do not have credit rating by major rating agencies. Hence, it is important for financial institutions to develop the right credit-risk model to measure the risk rating of SMEs. The ability to assess risk rating is important in determining the required capital for a bank in line with Basel II requirements. SMEs have a different methodology when calculating the required capital since the risk ratings of SMEs are generally higher than large corporations (Santos, Aires and Moreira, 2007). Another measure of credit risk is the value at risk (VaR), which refers to statistical confidence with respect to the maximum amount of loss that the bank can endure in specific market conditions. Besides credit risk measurements, VaR is used in market risk measurement and as a major component of stress testing credit portfolios (Jorion, 2006). All these measures are important for valuing credit risk, which is an important element in creating credit risk models (Altman, 2001; Kao, 2000). Credit risk and credit default are important aspects of credit risk modelling along with credit ratings.

3.2 Credit Rating

As mentioned in the previous chapter, it is important to determine credit risk by assigning the right rating that estimates capital requirements in line with the Basel II accord (Altman and Sabato, 2007). The credit rating can be estimated in different ways. Most large credit ratings associated with sovereign credit and large corporations are conducted by international credit rating agencies such as Standard and Poor's, Moody's and Fitch (Featherstone et al., 2006). There are also some regional and local agencies that conduct services associated with rating SMEs. For example, the Saudi Credit Bureau (SIMAH) has announced its intention to create a rating agency subsidiary in order to perform risk rating services for SMEs in Saudi Arabia. Such organizations help lenders to assess the credit risk of SMEs (SIMAH, 2017).

On the other hand, banks use internal credit rating models to assess the credit risk for firms that do not have external ratings. These rating models can be developed internally or bought from developers. However, as appears later in this study, these models work like data shells. Programming the data and inputting the coefficients are more important for the success and functioning of these credit risk models. The success of internal credit models depends on the historical record of the bank portfolio. Over time, banks can update their internal credit rating models to have inputs for quantitative variables as well as qualitative variables (Grunert, Norden and Weber, 2005).

3.3 Credit Risk Models

After reviewing credit default in the context of credit risk modelling, I review the literature on the different types of credit risk models in order to determine the parameters of an ideal credit risk modelling approach. This chapter reviews the different types of credit risk modelling that can be used in SMEs lending. Based on the literature, credit risk modelling can be classified broadly into four categories. These categories are exploratory models, statistical-based model, market-based models and hazard-based models. The most widely used model in today's financial market is the statistical-based model, which is the same one used in my empirical project. This review covers these models as discussed in the work of Datschetzky et al. (2005), Einarsson (2008) and Lin (2007); see figure 2.

3.3.1 Exploratory models

Exploratory models are considered the basic category of credit risk modelling. They are based on historical dealings of obligors that derive mostly from non-numerical variables. Exploratory models include classical rating questionnaires, qualitative-based systems models, intelligent-based systems and fuzzy logic systems.

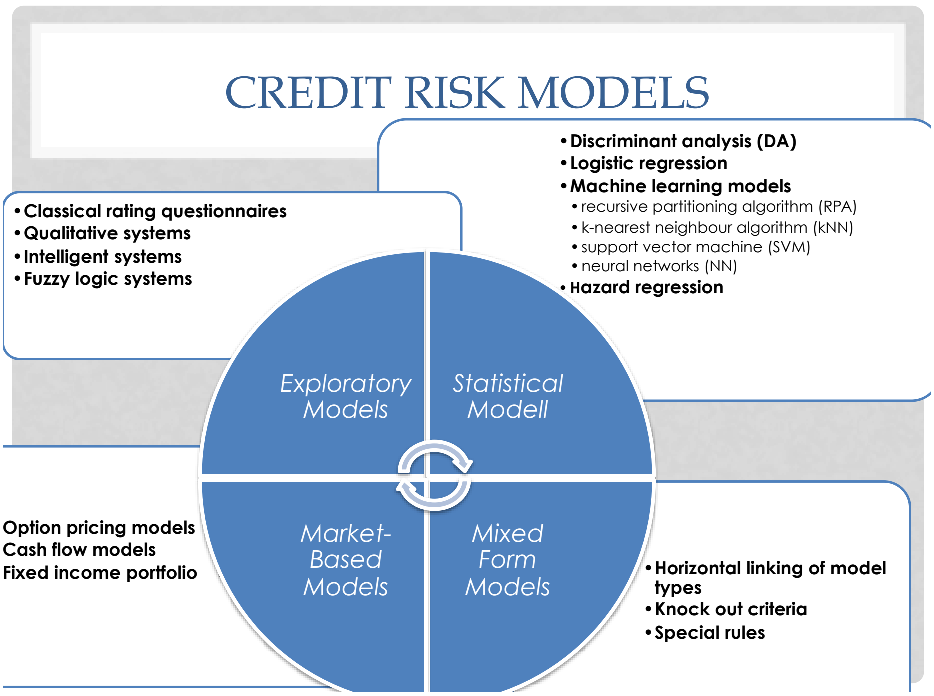


Figure 2: Credit risk models

Classical rating questionnaires are basic types of models that derive from a scorecard. The scorecard assigns weights to each qualitative answer the borrower gives.

The answers are tallied to devise a rating score in which the highest score refers to the best rating or opposite, depending on the qualitative arrangement of the scoring system (Dong, Lai and Yen, 2010). Some of the criteria included in the scorecard are net income, current ratio, leverage, type of business, the number of years, legal structure, quality of the auditor, etc.

The quality of the external audit and its ability to qualify a firm's data can be one of the variables for predicting a firm's bankruptcy, as has been empirically tested in a study on U.K.'s listed firms in the 1980s. Some results support the relationship between the presence of auditors' qualifications. This can be one of the scoring points embedded in the classic rating questionnaire (Citron and Taffler, 1992).

Qualitative systems: The qualitative-based approach is one of the earliest used rating methods. It is employed before the use of quantitative variables. In such systems, banks assess the credit worthiness of each factor and assign a registered grade for each customer. The innovation in data mining and the development of statistical techniques that combine quantitative and qualitative analysis have decreased lenders' dependence on qualitative systems (Bratko and Šuc, 2003). For example, credit risk assessment can include qualitative analysis regarding the succession risk, inventory hazard risk, performance risk, management and owners' succession risk, payment risk and high debt vs. tax saving.

Most of the literature highlights the benefits of high debt compared to high equity as a kind of qualitative variable. Return on equity increases as firms increase leverage. This is obvious as the required rate of return on loans is lower than the required rate of return on equity. Moreover, increasing a firm's debt reduces taxes on the firm, which directly benefits it. Loans work as a tax protection instruments for firms compared to those that barely carry debt on their balance sheet. On the other hand, studies have demonstrated the fact that high debt increases the chances of firms having difficulties and not being able to pay obligations as a result of low capitalization. Most SMEs have low capital bases and are exposed to high risk associated with debt. The fact that a firm can be exposed to difficult market dynamics means that it needs funding to meet urgent payments. The literature opens a controversial argument that the benefit of saving on taxes associated with increasing debt can be wiped out compared to the benefit of having high equity and being able to face difficult market conditions that need high equity. This qualitative assessment can be viewed as part of the qualitative factors for such type of models (Molina, 2005).

Intelligent systems: Intelligent systems, commonly called experts system in the literature, are expletory models that have problem-solving capabilities such as artificial intelligence. They are capable of analysing situations and making decisions intelligently like credit officers (Lin, 2007). These systems are able to analyse credits based on the well-known five Cs of credits that include character, capacity, capital, collateral *and* conditions (Haron and Shanmugam, 1994).

Fuzzy logic systems: Fuzzy logic systems combine both intelligent-based systems and fuzzy logic systems. They can artificially assess and solve credit situations. Fuzzy logic systems have outcome mimics to handle partial truth situations (Wu et al., 2011). For example, these fuzzy logic systems have embedded logic that is introduced to assign percentages for true decisions such as leverage ratio. In these situations, if the leverage ratio is below 1x, then the logic system reveals an acceptable outcome. On the other hand, if the leverage ratio is above 3x, then the logic system reveals an unacceptable outcome. If the leverage ratio is between 1-3x, then the logic system will result in a somewhat acceptable outcome. In these types of systems, non-quantitative variables are often applied to find the answers based on hurdles and expert analysis (Chen, Huang and Lin, 2009).

3.3.2 Statistical models

Unlike exploratory models that are based on historical, qualitative data, statistical models use empirical data that can include either quantitative or qualitative variables. Statistical models are the most commonly used models in the field of credit risk modelling. Statistical models include discriminant analysis models, logistic regressions models and other statistical models that incorporate machine-learning methods and hazard regression models. I review these types of statistical-based models with special emphasis on the discriminant analysis and the logistic regressions models (Freedman, 2006).

Discriminant analysis (DA): Discriminant function analysis is a statistical model to project a binary dependent variable by independent variables that can be discrete or continuous. Ronald Fisher developed the mathematical origin of this model in 1936 (Kim, Magnani and Boyd, 2006).

Discriminant analysis became popular after Altman implemented it in 1968. Subsequently, it gained popularity for predicting entities' default risk. The model includes the use of financial figures. The discriminant analysis is an applied Z formula that has several financial coefficients as follows: $Z = 0.12X1 + 0.14X2 + 0.033X3 + 0.006X4 + 0.999X5$, where X1 represents working capital; X2 represents retained earnings; X3 = EBIT; X4 = equity market value / total debt; X5 represents sales; X1, X2, X3, X5 are divided by total assets. The Altman Z score model is interpreted as follows:

2.99 < Z-score means that firms have a low probability of bankruptcy;

1.81 _ Z-score _ 2.99 means that firms have a medium chance of bankruptcy;

1.81> Z-score means that firms have a high probability of bankruptcy. (Einarsson, 2008; Altman, 1968)

In the same period, Taffler in 1982 applied the multivariate method to predict U.K. entities' defaults. His model used the following updated variables: (1) earning before tax / short term liabilities; (2) current assets / liabilities; (3) short term liabilities / total assets; (4) revenues / total assets.

Models that are based on accounting information input correctly can reveal accurate results when it comes to a firm's failure and exposure to bankruptcy risks (Taffler, 1983). Multiple discriminant analytic (MDA) models can be exposed to a certain degree of error depending on many factors related to the economic dynamics surrounding the firm and the industrial segment in which it operates. Because of those errors, results can be inconsistent (Mensah, 1984). There could be some issues when it comes to using statistical models for bankruptcy prediction. The models might not be useful when it comes to developing hypotheses. This depends on the variables used in testing (Dietrich, 1984).

Taffler has studied the application of default models on U.K. firms in several ways. He applies the Z scores depicting firms' exposure to default risks. He also describes the application of models on manufacturing and distribution firms. His study describes the twist discriminate model and the applications of these different models to the U.K.-based firms (Taffler, 1984).

Based on Zavgren's (1985) study on American firms for a five-year period before they defaulted, the predictability model can be useful. In some cases, discriminant analysis can be used; in other cases, the conditional probability approach can be used. The use of the models depends on the target.

Structural understanding in the prediction of policy changes coincides with the use of DA in several economic scenarios (Lo, 1986). It is obvious that the delay in submitting financial statements is one of the indicators of the probability of default from the lender's perspective. This happens as a lender becomes less aware of incidents within the defaulting firm and is not able to determine the firm's performance from the financial figures. Such behaviour can be one of the important variables in predicting bankruptcy especially for small entities (Keasey and Watson, 1988). This trend is more obvious with small firms than large firms.

Based on Financial Accounting Standards Board (FASB) [6] standards, the perceived increase in discretionary financial reporting behavior and the increase in unrecognized assets and obligations have great effects on the prediction ability of accounting variables over time. This supports the hypothesis that time and changing economic dynamics have a great influence over the bankruptcy prediction techniques highlighted in the literature (Beaver, McNichols and Rhie, 2005).

Altman (2005) has used the MDA method and has applied it to emerging corporate bonds. His model applies to value estimation on both manufacturing and non-manufacturing companies regardless of the ownership structure. The model is a good predictor of value in emerging markets and contains credit variables that could be applied to predict scoring and be compared to agency scoring. The model has been applied to Mexican companies covering the 1994 period. Altman's (2005) model uses the following variables: working capital as a percentage of total assets, retained earnings as a portion of total assets, operating income as a percentage of total assets (in some cases it is called

[6] Established in 1973, the Financial Accounting Standards Board (FASB) is an independent, private-sector, not-for-profit organization based in Norwalk, CT that establishes financial accounting and reporting standards for public and private companies and not-for-profit organizations that follow generally accepted accounting principles (GAAP) (FASB.org, 2017).

the gross profit margin) and book value of equity divided by total liabilities (Altman, 2005).

The Altman's Z-score model has been used on non-listed entities to predict their defaults. The model uses the following variables: net working capital / total assets, retained earnings / total assets, EBIT / total assets, equity / total liabilities and sales / total assets. Altman and Hotchkiss, in their 2011 study, have tried to answer the question of the recently adopted landmark legislation, particularly the Dodd-Frank Act's Title II (Receivership), which governs the resolution of systemically critical institutions.

Logistic regression: Logistic regression is a regression model in which the dependent variable Y can take the binary value of either zero or one. Zero represents non-defaulted firms and one represents defaulted firms. The following is the logistic regression model equation where: Y = 1 if the firm has defaulted and Y = 0 if otherwise (Baum, 2006):

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 \ldots.$$

The above equation that Ohlson (1980) presents is based on logistic regression. Unlike linear regression, which assumes a continuous dependent variable, logistic regression operates with discontinuous independent variables. The assumption is that the dependent variable Y has linear dependence on the independent variables x1, x2, x3, x4…. etc.

The method of logistic regression is considered one of the best if not the best method for predicting default since predicting default leads to a binary answer (default, or non-default, yes or no etc.). The outcomes, which are referred to as Ys in this research, are called dependent variables since the outcomes depend on many variables referred to as Xs. In terms of scoring and data coding, the logistic model is assigned a score of either zero or one. In multiple research studies, the outcome can be called the probability of default or bankruptcy prediction (DeMaris, 1995).

Ohlson (1980), a pioneer in developing models based on logistic regression, uses the method on both quantitative and qualitative variables. The model has been applied to U.S. entities covering the period of 1970-1980. The portfolio contains a sample of 2,163 entities with 4.85% defaulting entities and 95.15% non-defaulting entities. The model utilizes several coefficients (variables) that include: (1) the natural logarithm of (assets / price index); (2) liabilities / assets; (3) net working capital / assets; (4) current liabilities / current assets; (5) liabilities > assets with one assigned value, otherwise zero; (6) net income / assets; (7) funds provided by operations / liabilities; (8) income for past 2 years < 0 equals 1 otherwise 0; and (9) income increase / absolute income increase. The natural logarithms of some of the above variables enter the model. The result from their model is 30% more accurate than normal large cap models in default prediction.

The use of the logistic regression method in default prediction field started to become dominant after the recognition of some of the drawbacks associated with multiple discriminant analysis (MDA) method. Based on the literature, the use of MDA method in predicting default is not practical. Unlike in logistic regression methodologies, the alpha (constant) variables in MDA methodologies cannot be easily explained and are restricted when it comes to applications. As mentioned, Ohlson (1980) is the pioneer in using logistic regression methodologies to predict defaults based on US sample entities.

Classification accuracy in bankruptcy models has been tested using linear discriminant analysis (Hamer, 1983). Zavgren (1983) applies logistic regression methodologies to predict entities' bankruptcy. He analyses the significance of the variables.

Similarly, Altman and Sabato (2007) continue the trend of using the logistic regression method. The model applies to 2,000 U.S. SMEs for the period 1994-2000. They follow a sound method in filtering down variables. They start with five different categories including liquidity, leverage, profitability, coverage and activity ratios. Each category includes two variables. They reduce the variables to the following five in order to avoid redundancy: earnings before interest, taxes, depreciation and amortization (EBITDA) (Rhyne, 1979) over total assets; short term debt over book value of equity; retained earnings by total assets; cash as a percentage of total assets; and EBITDA over interest expenses (or the debt service coverage) (Altman and Sabato, 2007).

Other researchers such as Shumway (2001), Grice Jr., Dugan and Grice, (2003) and Becchetti and Sierra, (2003) also apply the same default prediction methodologies to their samples.

Behr and Guttler (2007) include the application of logistic regression method on 485 German SMEs. Besides using quantitative variables, the model includes significant qualitative variables such as business sector, legal entity structure and the geographic location of the entity's headquarters. As a result, the model effectively estimates the cost of borrowing.

Researchers have also tested the effectiveness of some of the leading pioneers' default prediction models. They have analysed the performance of these models in periods other than the period when these models were originally applied. For example, Agarwal and Taffler (2007) have applied Taffler's (1983) U.K.-based z-score model and have tried to validate it 25 years after its development. The study highlights the continued feasibility of using the Taffler model for banks.

In another study (Kubíčková, 2015), Ohlson's U.S. logistic regression model, INO5 a Czech model[7] and Taffler's U.K.-based model are tested. The comparison applies to a 1996 Czech SMEs sample during the period of 2012-2013. The results indicate that there is homogeneity between the results of Ohlson's model and Taffler's model in 90% of the entities. However, results are less homogeneous in IN05 and Altman's model and are limited to only 30% of the sample entities.

Altman, Sabato and Wilson (2008) have studied a model that includes financial and non-financial variables. The model applies to SME samples consisting of over 5.8 million accounts of non-traded entities, of which 66,000 defaulted during the period of 2000-2007. The financial variables include but are not limited to: retained profit / total assets, quick assets / current assets, net cash to net worth, change in net worth and change in retained profit. The model also involves significant non-financial variables such as legal action by lenders to recover unpaid debts, company filing histories, comprehensive audit reports and firm-specific characteristics.

It is worth mentioning that regardless of the method being used, MDA or logistic regression, the classification accuracy that is discussed in the analysis chapter is the same.

Machine learning models and other statistical models: Machine learning models are statistical rating models that depend on computer programming such as the recursive partitioning algorithm (RPA), k-nearest neighbour algorithm (kNN), support vector machine (SVM) and neural networks (NN). The following section covers the several types of machine learning models.

Recursive partitioning algorithm (RPA): Recursive partitioning algorithm (RPA) is a model that can be used for financial analysis in measuring a firm's default

[7] INO5 is a study that was conducted on Czech based companies (Kubíčková, 2015).

predictability. The model is based on pattern recognition, which has attributes of both the classical univariate classification approach and multivariate procedures. In some cases, the model can have better predictability compared to discriminant analysis. Such rating models are based on decision trees (Frydman, Altman and Kao, 1985).

***k-nearest neighbour algorithm (kNA)*:** K-nearest neighbour algorithm is a machine learning model that assumes the average of the dependent variable of the k observation. In these models, the value of k through two options has to be selected with nearest neighbours. Selecting k is a function of two options: bias and variance. The choice of k depends on the compromise one wishes to make between bias indicated by small k and variance with larger k (Sun and Huang, 2010).

***Support vector machine (SVM)*:** Support vector machine is a model that is related to discriminant analysis. The model has controlled prediction models with related predictive algorithms. The SVM algorithm constructs models with different distributions (Lo, 1986).

Neural networks (NN): Neural networks are computer science models that depend on gathering neural links, similar to human brain. They can program any information that can contribute to a sound rating model (Trigueiros and Taffler, 1996). Based on an Italian study between the 1980s and 1990s, linear discriminant analysis and neural networks have high accuracy in predicting bankruptcy. However, the model places special emphasis on neural networks due to the ambiguous nature of algorithm application (Altman, Marco and Varetto, 1994). There has been a historical evolution in reporting default predictions in the Auditing Standards Board’s SAS 34 and SAS 59; because of a difference in auditor reporting, the professional standards were tightened by SAS 64 (Carcello and Hermanson, 1995).

Hazard regression: Hazard regression models are statistical models that are called survival-based credit scoring models. These models entail the use of descriptive inputs that impact the survival time. In some cases, hazard models are called survival-based scoring models or credit scoring models. Lando (2004) uses proportional hazard regression to predict the time until a security defaulted. Denis and Sarin (1997), Pagano and Panetta and Zingales (1998) combine time change factors, or descriptive variables, that alter with time and are used for default projection.

3.3.3 Market-based models

Market-based approaches include option pricing models, cash flow models and fixed income portfolio analysis. Unlike statistical models, these models do not depend on empirical data. They depend, rather, on market-based data. The following section reviews these types of models.

Option pricing models: The option-pricing model is rarely used and has been described as an accidental pricing model. These models depend on volatility, time and some financial variables such as leverage. According to Hillegeist et al. (2004), the applied concept is in line with the early developers Black, Scholes and Merton.

In a study to compare the performance of two default models—namely Altman's (1968) Z-score and Ohlson's (1980) O-score, which are based on financial variables—Hillegeist et al. (2004) reveal that these bankruptcy prediction models perform lower in terms of predation compared to a model based on the Black-Scholes-Merton option-pricing model. The results strongly encourage the use of the market-based model rather than historical, financial report-variables-based models. However, this argument still needs validation, as certain market conditions could influence the results (Hillegeist et al., 2004).

Cash flow models: Cash flow models are rating methods that are similar to discounted cash flow approaches. These rating models discount the future cash flow of the obligor over certain time based on a certain discount rate (Einarsson, 2008).

Fixed income portfolio analysis: These models depend on pricing bonds based on the time value of money and considering the probability of default factors (Marchesini, Perdue and Bryan, 2004).

3.3.4 Mixed form models

Mixed form models are statistical models that are combined with other models. For example, expletory models can be combined with statistical models.

Besides the classical logit default predicting models, there have been efforts to apply mixed-based bankruptcy models that incorporate independently and identically distributed errors (IID). Empirical studies, to some extent, reveal the outperformance of these mixed logit models (Jones and Hensher, 2004).

Using both market and accounting information to predict bankruptcy has become the trend. Bauer and Agarwal (2014) have conducted a study on U.K.-listed entities covering 30 years for the period of 1979-2009. The resulting receiver operating characteristics (ROC) curve show that the hybrid predicting models outperform the classical accounting models (Bauer and Agarwal, 2014). The followings are some structures of integrating different types of models. These are horizontal linking of model types, overrides, knock-out criteria and special rules.

Horizontal linking of model types: These include the mixing of quantitative and qualitative data horizontally (Bellalah, Zouari and Levyne, 2016).

Overrides: These models are based on credit officers altering results through the enforcement process (Chappell, Maggard and Higgins, 2013).

Knock out criteria: Knock out criteria are models that use filtering before assessing the credit risk. For instance, credit criteria may include negative industry lists (Khil and Suh, 2010).

Special rules: Special rules depend on adding rules to the model such as a start-up business, type of business, number of years, etc. (Einarsson, 2008).

There are other models that are developed by international banks such as KMV, the portfolio manager model and KRM (Reisz and Perlich, 2007). A study (Oderda, Dacorogna and Jung, 2003) tests the validation accuracy available in the widely-used market-risk-rating models, KMV Credit Monitor and RiskCalc from Moody's. The study tests the reliability of these models over time based on data provided by users. The empirical test reveals a positive result and the high reliability of these commercial risk-rating models. In fact, these models are reliable enough to predict the bankruptcy risk of SMEs before default by almost a year. This can be valid during certain economic conditions and under a normal environment (Oderda, Dacorogna and Jung, 2003).

3.4 Factors to Consider in SMEs Credit Risk Modelling

Unlike the previous researchers who have used accounting and financial ratios, Merton (1974) has used the market-based approach. He presents the theory of the risk structure of interest rates that depend on the probability of default.

Many authors have studied bankruptcy theory and have presented empirical results that lead to solutions before firms get exposed to bankruptcy. A firm can have several options in front of it in order to avoid issues of failure. The mergers can offer a viable solution for firms before they are exposed to issues and ultimately leave the market (Shrieves and Stevens, 1979).

The financial information in market published, annual reports shows that firms' financial ratios lead investors to certain perceptions about the market. Tests that involve two-factor models to predict a firm's performance and probability of defaults last for one year. On the other hand, tests that are based on single-factor models are in line with studies that focus on market efficiency (Altman and Brenner, 1981).

In a study that is based on stock market performance, Wilcox's gambler's ruin model, along with the use of trading ideas to avoid bankruptcy and achieve a solid performance, have been applied in the context of bankruptcy avoidance (Katz, Lilien and Nelson, 1985).

Non-nested hypotheses for bankruptcy prediction through chi-square are used in credit risk (Vuong, 1989). Stock market divestment is a reliable predictor of a firm's probability of default, as tested in many empirical works. Such divestment is an important factor to consider in market-based approach models (Keasey and Watson, 1991).

Considering the application of the Altman and Sabato (2007) and Ohlson (1980) models when it comes to bankruptcy prediction, U.S. studies have proven that their use has waned in recent years compared to times when they were originally used. This is clear with respect to the use of variables in statistical models (Begley, Ming and Watts, 1996). The literature exhibits the importance of conducting international surveys to validate the accuracy of default predicting models (Altman and Narayanan, 1997).

Incorrect information and mitigating factors of audit surveys can influence firms that are in the process of defaulting on debt (Mutchler and Hopwood, 1997). There is a relationship between auditors growing concern and loss function in situations involving bankruptcy prediction techniques (Louwers, 1998).

Some main credit-risk-pricing approaches including the structural (firm-value) and the reduced-form models have evolved in pricing credit risk and estimating bankruptcy probabilities (Kao, 2000).

Studies have proven that strategic planning is important for firms in order for them to grow in the long run. This is an important factor to include as a qualitative variable in credit-risk modelling. It is important for SMEs to define their strategies in order to achieve long-term plans. Successful firms spend time in creating their strategies and link their strategies to their long-term goals. Most bankrupt or almost bankrupt firms fail to create long-term strategies. Some firms create strategies but they fail to update them. It is easy for firms to create strategies; however, it is also important for them to implement their strategies. Most firms that fail to implement their strategies are exposed to default in paying obligations and exposed to bankruptcy. Sudarsanam and Lai's (2001) study of 166 UK firms consisting of successful and defaulting firms between 1985-1993 supports the notion that strategy implementation is important for firms. The study reveals that defaulting firms spend more of their time and efforts on defensive strategies than on planning. On the other hand, successful firms spend more of their efforts on growth-related strategies and market-intelligence related strategies.

The origin of a loan as determined by its currency is essential to assess the foreign exchange exposure risk of an SME. It is important for SMEs to hedge their exposures against foreign exchange fluctuations and not to engage in products that are not fit for their operations. Many firms that have failed to protect the liabilities that are priced in foreign currencies other than their home currency. Some defaulted firms fail to protect themselves if they borrow in currencies other than their base currencies. This was mostly evident within Asian firms during the devaluation stage took place in times of the Asian crisis (Allayannis, Brown and Klapper, 2003).

When it comes to calculating risks and applying risk-rating models, it is important for financial institutions to ensure the soundness of these risk models in order to avoid taking the right provision and the optimal capital adequacy. This is in line with Basel requirements for banks. The accuracy and the importance of making sure risk is measured to the best possible measurement is essential. The test of the reliability of these models should be conducted periodically as the portfolio parameters change over time. Besides internal checking and developments, it is important to use external auditors to ensure the accuracy of these risk-rating models. The use of external risk rating models developed by vendors is widespread; however, most of these risk-rating models are working as shell models, i.e. it is important for those financial institutions to update these models by incorporating the right quantitative and qualitative variables over time (Ferguson and Shockley, 2003).

There are market variables that measure solvency-to-equity market values and take into account the betas. This falls in line with the single beta capital asset pricing model (Ferguson and Shockley, 2003).

Most of these models have been tested on equities risk. On the other hand, some businesses such as high-yield bonds for firms may have a higher probability of going bankrupt since there is no clear method for forecasting their default. This argument is based on the evaluation of every bankruptcy prediction model, which has indicated that there is no suitable model for the prediction of the default on high-yield bonds (Marchesini, Perdue and Bryan, 2004).

The literature extends to comparing statistical models' performance over time. For example, in a study based on firms for the period 1962-1999, Shumway's (2001) model shows better performance compared to Altman (1968) and Zmijewski's (1984) studies. This is because of the fact that the first model is based on monthly reported variables compared to annual reported financial figures. The frequency of reporting could lead to stronger predictability power in contrast to annual reported data. Industry segmentation also has high influence over the prediction (Chava and Jarrow, 2004). The same study supports market-based models, such as Black and Schole, compared to historical accounting-based models.

Balcaen and Ooghe (2006) identify some issues with the said statistical techniques. They claim that the techniques are highly influenced by the collinear patterns of variables and the non-consistency over time influenced by changing economic conditions. They also claim that these statistical models tend to ignore the time-factor holding other things constant that have an effect on bankruptcy behaviour. The limited objective of these models focusing on default risk could influence predictability power. Most of these statistical models tend to focus on quantitative variables and ignore other qualitative variables that could determine the success or failure of firms (Balcaen and Ooghe, 2006).

Balcaen and Bogno (2006), in their model of the market-based framework for bankruptcy prediction, estimate the defaults of 5,784 businesses between 1988 and 2002 using entities that are market-based. Their result reveals better default estimation than techniques employed in option pricing. According to them, default probabilities indicate a perfect calibration and discriminatory power as compared to the ones that are inferred in the standard Black and Scholes. They are also better predictors than accounting based models over the long run (Reisz and Perlich, 2007).

The hypothesis related to the return associated with high risk of default has been examined in the literature of SMEs. A study by Campbell, Hilscher and Szilagyi (2008) shows that this hypothesis has been proven contrariwise. The study proves that firms with a high risk of default exhibit a low rate of return on the investment over time.

One of the market irregularities associated with holding long-term positions in firms that have high default risk and have been able to sustain market difficulties has proven to be a high yield investment strategy, as evident through a study (Avramov et al., 2013). The key factor is that firms have to be able to sustain adverse market conditions (Avramov et al., 2013).

Agarwal and Taffler (2008) compare market-based default prediction methodologies against accounting-based prediction models in the U.K. context. The study concludes that the two methodologies cover different characteristics of default risk. Despite the minor difference in the results, using the z-score method indicates that there is drastically greater bank profitability in situations of differential decision error costs and competitive pricing.

A Finish study tests the effect of using fair value accounting as part of International Financial Accounting Reporting Standards (IFRS). The resulting accounting ratios changed, which led to alterations in the prediction model (Lantto and Sahlström, 2009).

A study (Wu et al., 2010) recommends the use of capital market data such as excess stock returns and stock return volatility. These along with the application of the

Black-Scholes-Merton option-pricing model can be innovative tools in predicting defaults (Wu et al., 2010).

Grunert and Norden (2012) study the use of soft skills on a sample of U.S. and German entities. The variables include work experience, age and the entity size, which means that the natural logarithms[8] of the entity revenue have more effect (Grunert and Norden, 2012). In the empirical project chapter of this dissertation, the size of the firms serves as one of the financial variables to build the model. One of the important variables is the revenue of the entity.

Based on the reviewed bankruptcy prediction literature, my research model follows Altman and Sabato (2007) by incorporating some financial variables provided by the bank sample portfolio, taking into consideration the inclusion of some qualitative variables.

[8] The natural logarithm of x is generally written as $\ln x$, $\log_e x$, or sometimes, if the base e is implicit, simply $\log x$ (Vinso, 1981).

4. DATA AND DESCRIPTIVE STATISTICS

In this chapter, I review the historical defaults of the sample portfolio and provide descriptive statistics of the data. After that, I define the proposed model variables and compare them to the literature. The data for this research has been collected from the SME portfolio of one of the major commercial banks in Saudi Arabia. The bank has several products that are offered to corporate clients as well as retail, individual clients. The bank has a sizable SMEs portfolio as part of the corporate banking department.

4.1 Data

The data of the SMEs portfolio consists of 1,814 entities for the period between 2001-2011. It is to be noted that the bank has provided me only with the data of its SMEs portfolio up to 2011. Moreover, the bank started covering the SMEs segment back in 2000 and it has witnessed several issues with the portfolio. The data observations were put into a time series setup. The portfolio of these SMEs represents entities from different business sectors with annual turnovers capped at Saudi Riyals 50 million (equivalent to 13.3 million in U.S. Dollars). This amount is in line with SMEA's definition for SMEs released in 2016 (Ministry of Commerce and Investment, 2016)[9].

In analyzing the portfolio period from 2001-2011, some entities witnessed growth in their annual revenues exceeding the bank's SMEs criteria and some of these entities immigrated from the bank's SMEs portfolio to the bank's mid-cap or in some cases large-cap portfolios. This movement is typical since businesses grow over time based on prevailing market conditions. Going through the database of the sample, in general, most

[9] With the exception of this target market revenue criteria, one entity was included within the portfolio in 2010 with annual revenue of 142 million in Saudi Riyals (approximately 38 million a year in U.S. Dollars); this exception is based on the bank's SMEs target market criteria. For the purpose of this study, the entity is considered a medium-size entity.

entities have 11 years of observations. The data contains 14,727 firm-year observations. Out of the 14,727 observations representing 1,814 entities, there are 712 default observations representing 297 defaulted entities. Based on the literature, this is considered a quite sizable data set in the developing world; the size is also in line with Ohlson's study in 1980. His model has been applied to U.S. entities covering the period 1970-1980. His portfolio contains a sample of 2,163 entities with 4.85% defaulting entities and 95.15% non-defaulting entities (Ohlson, 1980). Table 6 displays the number of defaulted entities in each year where the year 2004 seems to have the highest percentage of defaulted entities at 6.41% compared to an average default rate of 4.83%. The second highest default year was 2005 with average 5.29% defaults.

The portfolio is considered low in terms of the percentage of default if compared with Altman's 1968 portfolio in which 50 percent of the sample portfolio includes defaulted firms (Altman, 1968). The year 2001 had the lowest defaults at 0%; this is because the SMEs lending in the bank started in 2000, so the firms did not have time to default. The second lowest default year was 2002 at 2.54%. Notably, the bank experienced a learning curve for the SMEs lending portfolio as it had been mainly conducting large, corporate-sector loans. The rate of default is relatively high compared to the corporate banking segment and the department had to witness some losses before it paused its business in order to understand the behavior of the portfolio and assess the credit risk. This study could guide Saudi banks on how to handle the SMEs portfolio more effectively.

Table 6. Sample Observations and defaults

Year	No. of Firms	No. of Defaults	Default Rate (%)
2001	346	0	0%
2002	788	20	2.54%
2003	1121	65	5.80%
2004	1232	79	6.41%
2005	1397	88	6.30%
2006	1494	79	5.29%
2007	1575	67	4.25%
2008	1630	61	3.74%
2009	1662	74	4.45%
2010	1686	90	5.34%
2011	1796	89	4.96%
Total Obs.	14,727	712	4.83%
No. of unique firms	1814		
Total Obs./Firms	8.12		

Notes: This table shows the collection of the data sample for SMEs portfolio in one of the major Saudi bank for the period of 2001-2011. The first column lists the sample year. The second column shows the number of sample entities in a given year. The third column presents the number of the defaulted entities in a given year. The last column represents the percentage of defaulted firms in a given year, which is calculated by dividing the number of defaults in a given year by the number of firms in a given year. The total sample years are 14,727 observations represented by 1,814 unique entities. In the bottom of the table, 8.12 represent the average number of years for each entity, which is calculated by dividing the total observations by the number of entities.

In line with Altman and Sabato (2007), Figure 3 describes the data based on the revenues class in which small businesses are sample entities with annual turnover or revenues less than 31 million Saudi Riyals, representing 64.43% of the sample portfolio. On the other hand, medium-sized entities are those entities with annual revenues between SR 30-100 million representing 35.57% of the sample portfolio. Figure 3 presents the sample portfolio business segmentations where 51.21% of the entities are trading entities. This is not unusual since the Saudi economy depends on imports. Light manufacturing and other businesses, mainly services, represent 31.96% of the sample portfolio. Contracting represents the remaining percentage of the sample portfolio at 16.83%.

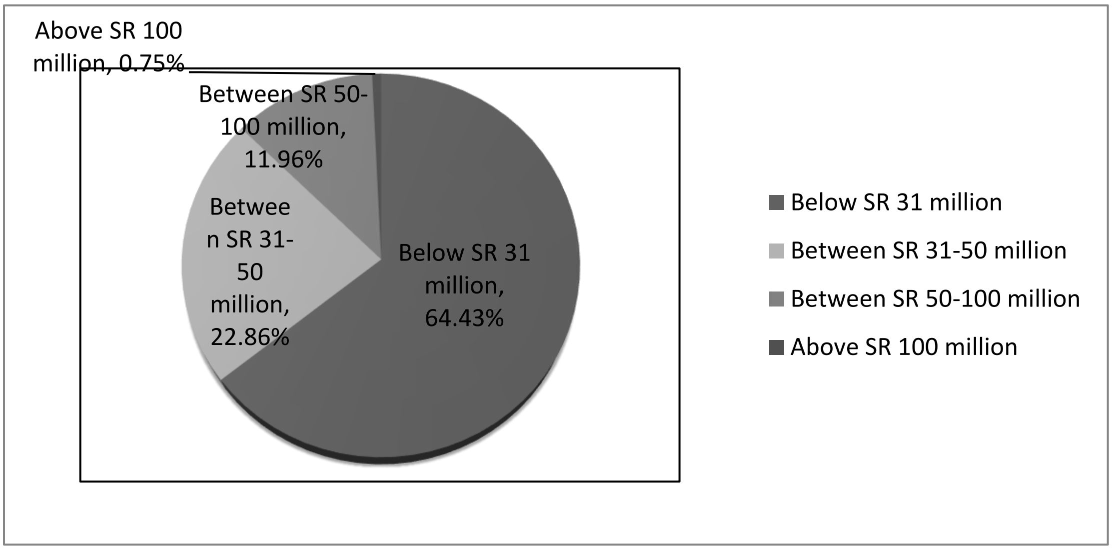


Figure 3: Distribution of revenues in the Saudi SMEs sample portfolios

4.2 Variables and Descriptive Statistics

In line with the literature, there are large numbers of possible variables that can be used in predicting entities' possible payment default. This research incorporates 21 variables that are captured from the entities' annual financial statements and some qualitative information about the entities. After reviewing the literature, the 21 variables have been identified and filtered down to 12 variables, using some statistical methodologies such as principal component analysis (PCA). Following Grunert et al. (2005), the study includes some qualitative variables such as the legal structure of the company (sole proprietorship or partnerships such as a limited liability company and closed joint stock company); however, closed joint stock companies are rare for small businesses. The geographical location of the business in Saudi Arabia appears as the central region, eastern region, or western region. This is parallel to Behr and Guttler's (2007) study on 485 German entities, which includes significant qualitative variables such as business sector, legal entity structure and the geographic location of the entity's headquarters (Behr and Guttler, 2007).

Obviously, the older the firm, the more maturity it can enjoy and thus, it has less of a probability of default. The combined mean age of the sample entities in the portfolio is 15 years, whereas the mean age of the defaulted firms is 11 years. The age of the firm by its own has not been used as a variable in the literature. It has been, however, used as a variable in qualitative models (Molina, 2005). The number of employees also does not appear as a variable since there are many small businesses in Saudi Arabia that work as contractors in operations, maintenance and the construction business segments, which have a large number of employees. This can be misleading since a large number of employees can give an SME the appearance of a large business. Figure 4 outlines the distribution of business sectors of the Saudi SMEs portfolio.

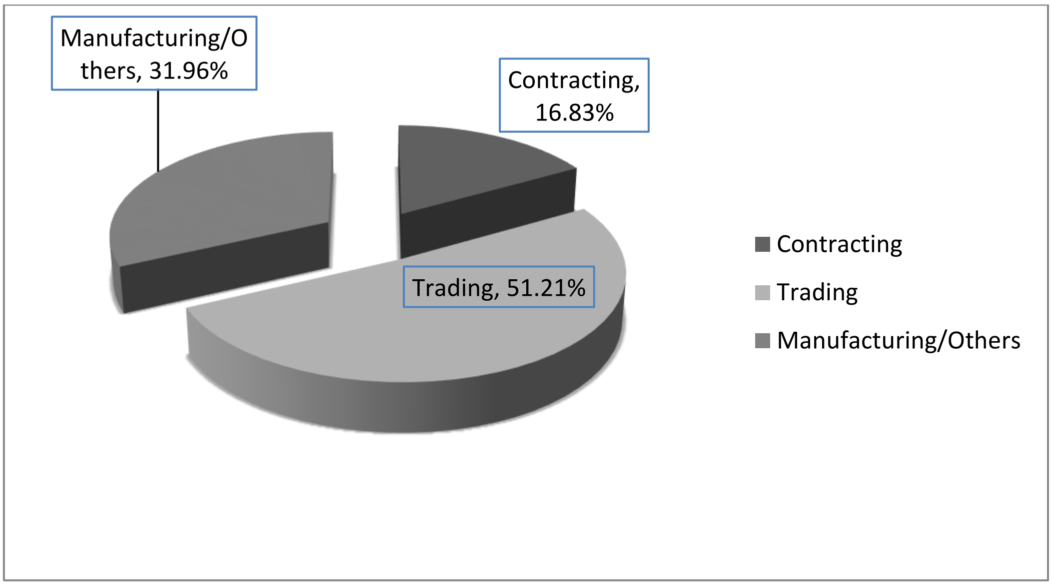


Figure 4: Distribution of business sectors of the Saudi SMEs sample portfolios

This figure illustrates the distribution of business sectors. At 51.21%, most of the sample entities work in the trading business sector. The manufacturing/other sector represents 31.96% of the sample portfolio. Contracting represents 16.83% of the sample portfolio.

I have added some qualitative variables that could have some impact on the predictability of an entity's default. These include the status of the entity's financial statements and whether it has been audited by an external auditor or in-house by the management of the entity. The quality of an external audit and its ability to qualify a firm's data can be one of the variables for predicting a firm's bankruptcy, as empirically tested through a study done on U.K.-listed firms in the 1980s. Some results support the relationship between the presence of the auditors' qualifications[10] (Citron and Taffler, 1992). Other qualitative variables defined in Table 7 include customer and/or supplier concentrations. The availability of raw materials to manufacture goods is an important element to consider in addition to mitigations for business interruption risk and issues with suppliers and agencies. All of these factors have to be taken into consideration to mitigate the credit risk associated with a borrower's ability to pay its debt (Kuo et al., 2011; Santos et al., 2007).

An entity can be viewed as customer-concentrated if it has sales/revenues that are highly concentrated among a small number of clients (less than five clients) and/or more than 50% of the entity's sales/revenues are generated by less than five clients. Similarly, an entity can be viewed as supplier concentrated if its supplies/payables distribution are highly concentrated among a small number of suppliers that are less than five suppliers

[10] A qualified opinion issued after an audit is performed by an external auditor about the information published by the business, which does not comply with certain accounting standards (Investopedia, 2016).

and/or more than 50% of the supplies are sourced by less than five suppliers. Concentrations indicate that the companies are in greater risk of bankruptcy.

Following the bankruptcy literature approaches, some financial variables carefully cover the size, profitability, efficiency, solvency, etc. of the businesses (Table 7).

This section expands on the definitions presented in Table 7. In finance, **equity**—sometime called owner's equity or shareholder's equity—is calculated as assets minus liabilities. There are several types and components of equity such as common stock, preferred stock, retained earnings, reserves, current account, etc. The estimation of equity valuation can be done through several financial techniques. For example, equity can be calculated based on the discounted cash flow technique, P/E ratio, or market equity multiples (Elias, 2010).

Revenue, sales or turnover is the amount that an entity makes from its ordinary business sold to clients. The revenue is measured in currency over a period of time such as a day, week, month, quarter, or year. There are several types of revenues such as commission, service revenue, royalty, fee, etc. In accounting, revenue is usually recorded if the service rendered or the good is delivered to clients. In some cases, revenue is called top line (Smoller, 1999).

Cost of goods sold (COGS) alludes to the conveying estimation of merchandise sold or services rendered over a specific time. COGS is related to the direct expense of selling the good or rendering the service. It excludes indirect expenses such as selling and general/administrative expenses. COGS includes expenses of procurement, expenses of transformation and various expenses rendered in conveying the inventories. COGS includes direct expenses such as fuel, direct labour expenses and delivery expenses (Elias, 2010).

Days receivables or average collection period is an indication of the number of days an entity needs to collect its credit sales or revenue. The figure is usually presented in days and is a sign of the health of an entity's credit policy, receivables and liquidity. It is calculated as follows:

*Days Receivables = Account Receivables / Sales * 360 (or 365)*

As a rule, high days receivables for an entity means the company has problems with its collection. Low days receivables mean most of the company sales or revenue are conducted on a cash basis. Most retail clients sell on a cash basis and have low days receivables figures. On the other hand, sometimes wholesaling is conducted on credit and tends to have a higher number of days-receivables. Yet days-receivables can be misleading. For example, if an entity conducts most of its revenue on a cash basis but sells some goods on credit at the end of the year when the days receivable is calculated, the calculation can indicate high days-receivables, which contrast with the company's general pattern of operation (Rhyne, 1979).

Days inventory usually refers to the number of days an entity stocks its inventory before selling it to clients. Like days receivables, days inventory is quoted in number of days. It can be calculated as follows:

*Days Inventory = Inventory / Cost of Goods Sold * 360 (or 365)*

In most cases, high days-inventory is not healthy since it means the entity could be witnessing a slowdown in its inventory turnover. However, this, too, can be misleading, as it might indicate that the entity is lagging behind high sales and is not able to stock enough inventory to meets its expected sales. Days inventory is seasonal and it varies when the ratio is calculated. For example, while the company may have healthy days inventory when it is efficient, it may purchase a major supply of inventory at the end of the year in order to meet expected sales. Calculating the ratio can be misleading as it might show a spike in the ratio at the end of the year due to the seasonality effect of having to stock higher inventory to meet new sales. Days inventory depends on the nature of the business and its goods. For perishable goods, it is better to have low days-inventory to avoid adverse results in the stock such as the expiration date (having products that cannot be used after the product registered expiration date). For durable goods that are not exposed to change in fashion, it is acceptable to have longer days of inventory. For a jewelry business, for instance, days inventory can be long, more than a year, because consumer taste remains unchanged and a drop in the value of the inventory causes little concern (Elias, 2010; Nelson, 1971).

Days payables measures the number of days an organization takes to pay its suppliers or service providers. It is calculated as follows:

*Days Payables = Payables / Cost of Goods Sold * 360 (or 365)*

Like days inventory and days receivables, days payable is measured in the number of days. In general, long days-payables means that the entity is enjoying good credit terms from its suppliers. On the other hand, short days payables means that the entity has a short number of days to pay its suppliers. This can be misleading, as the entity might want to take advantage of the discount terms from suppliers and tend to pay earlier. As such, it is a subjective figure. This ratio is also affected by the seasonality of inventory and the business’s relationship with suppliers. For example, there are cases in which an entity typically pays its suppliers early but pays later at the end of the year when it buys in bulk. Such inconsistencies might be misleading for interpreters. In cases when an entity enjoys a good credit term and hence, long days payable, it might receive an inflated leverage ratio. Sometimes, a high-leverage ratio can be a negative sign, but in the above case, it would not be (Knight and Berman, 2008).

In finance, **cash cycle** or cash conversion cycle is the number of days it takes an entity to buy its inventory, stock it briefly, then sell it by cash or credit to clients and finally pay back its suppliers. It is given in days as with days inventory, days receivables and days payables. Below is the most common equation for calculating cash cycle:

<u>Equation 1: Cash Cycle</u>

Cash Cycle = Days Inventory + Days Receivables – Days Payables

or

*Cash Cycle = (Inventory / Cost of Goods Sold * 360) + (Accounts Receivables / Sales * 360) – (Accounts Payables / Cost of Goods Sold * 360)*[11]

In general, it is better to have a short cash cycle for an entity, which indicates higher efficiency. However, there are many factors that affect the calculation of the cash cycle depending on each component of the formula. Conversion cycle is a seasonal figure that depends on the business nature. An excessive stocking policy can lead to a high cash cycle. A delay in receivables collection from a client can also lead to a long cash conversion cycle. There are cases in which the cash conversion cycle is negative and can be misleading as a result of longer days payable compared to days receivables and days inventory (Nelson, 1971; Elias, 2010).

Leverage ratio is the degree of an entity's obligations. It indicates the extent to which an entity is bearing obligations against its equity or assets. There are several ways to calculate the leverage ratio. It can be calculated by dividing short term debt over equity

[11] We can use 365 days instead of 360 days depending on the day's calculation basis.

or liabilities over equity. There cases in which some of the obligations are added in the numerators. Sometimes the ratio's denominator can be the entity's total assets. The most common way of calculating leverage ratio is as follows:

Leverage Ratio = Total Liabilities / Total Equity

The preceding formula is used for calculating the leverage ratio in this study. The ratio is called balance sheet leverage. In some instances, leverage can be calculated based on an income statement by dividing EBITDA by obligations.

In general, high leverage indicates negative signs, which puts an entity's liquidity at risk. An entity can be exposed to liquidity constraints and be unable to meet its obligations especially if it has a high leverage ratio. Leverage is a major component of capital structure and sometimes high leverage is used to reduce tax payments (Ghosh and Sherman, 1993).

Gross profit margin is a profitability measure given in a percentage and calculated as follows:

Gross Profit Margin = Gross Profit / Sales

The higher the gross profit margin, the better it is for an entity. The margin depends mainly on the gross profit and the entity's ability to increase it by saving on the cost of goods sold. The ratio depends on the type of business. The ratio is generally low when there is a high volume of sales as with food and low-priced retail products. On the other hand, the ratio tends to be high in low-volume, unit sales such as luxury items (Nelson, 1971).

Net margin or net income margin is also a measure of bottom-line profitability. High net margin indicates the high profitability of a business. It is calculated as follows:

Net Margin = Net Income / Sales

Net margin is quoted as a percentage. It depends on the nature of the business. For example, the net margin is usually low in high-volume sales businesses such as supermarkets. On the other hand, the net margin is usually high for low-volume businesses. Net margin is influenced by the currency value of net income. It is positively related to net income. There are many income statement items that influence net margin. For example, a lower gross profit or higher cost of goods sold can lead to a lower net margin. Non-direct cost items like selling and general/administrative expenses have an adverse effect on net income and hence, net margin. Financing costs and taxes can also lower net income and net margin simultaneously. In corporate finance and debt payment, net margin can be misleading since it is negatively influenced by non-cash items like depreciation and amortization. In those cases, it would be more accurate to look at EBITDA/sales. Besides being a profitability measure, net margin is considered a measure of efficiency where the higher the margin means higher efficiency in managing a business (Nelson, 1971).

Table 7: Variable definitions

Variable	Definition
Default (1/0)	A dummy variable that equals one if the firm has defaulted in paying its obligations to the bank and exceeded 90 days of not being able to pay its obligations; the variable equals zero if the firm has not defaulted in a given financial year and is still within the 90-day probation period
Equity Value (ln)	The natural logarithm of a firm’s book value of equity
Revenue (ln)	The natural logarithm of a firm’s annual reported revenue
COGS (ln)	The natural logarithm of a firm’s annual reported cost of goods sold
Age (ln)	The natural logarithm of the number of years since the firm started its business
Days Receivable (ln)	The natural logarithm of the number of days required for the entity to collect its credit sales from the market in a given financial year, calculated as: Account Receivables / Sales * 360
Days Inventory (ln)	The natural logarithm of the number of days the entity keeps its inventory before it sells stock to customers in a given financial year, calculated as: Inventory / cost of goods sold * 360
Days Payable (ln)	The natural logarithm of the number of days required for the entity to pay its payables to suppliers in a given financial year, calculated as: Account Payables / Cost of Goods Sold * 360
Cash Cycle (ln)	The natural logarithm of the number of days required for the entity to buy goods/raw materials, stock them, sell them and collect the cash from customers in a given financial year, calculated as: Days Receivables + Days Inventory - Days Payables
Total Facilities Ratio	Firm’s total credit exposure to its sales
Leverage Ratio	Firm’s total liabilities divided by its equity.
Gross Profit Margin	Firm’s gross profit divided by its sales
Net Profit Margin	Firm’s net income divided by its sales
Eastern (1/0)	A dummy variable that equals one if the firm is located in the eastern region of the country and zero otherwise
Western (1/0)	A dummy variable that equals one if the firm is located in the western region of the country and zero otherwise
Sole Proprietorship (1/0)	A dummy variable that equals one if the firm is legally structured as a sole proprietorship or establishment and zero if it is structured as a limited liability company
Contracting (1/0)	A dummy variable that equals one if the firm’s industry is classified as contracting and zero otherwise
Trading (1/0)	A dummy variable that equals one if the firm’s industry is classified as trading and zero otherwise
Audited (1/0)	A dummy variable that equals one if the firm’s reported financial statement in a given year is audited and zero otherwise
Concentrated Customer (1/0)	A dummy variable that equals one if the firm’s sales/revenues are highly concentrated among a small number of clients less than 5 clients and/or more than 50% of sales/revenues are generated by less than 5 clients; the variable equals zero if its sales/revenues are diversified among more than 5 clients and/or more than 5 clients generate more than 50% of sales/revenues
Concentrated Supplier (1/0)	A dummy variable that equals one if the firm’s suppliers/payables distribution are highly concentrated among a small number of suppliers less than 5 suppliers and/or more than 50% of supplies are sourced by less than 5 suppliers. The variable is zero if its supplies are diversified (not highly concentrated among less than 5 suppliers and/or 50% of supplies are sourced from more than 5 suppliers).

Notes: This table defines the financial and qualitative variables in the prediction model. The size variables include: equity value (ln), revenue (ln), COGS (ln) and age (ln). The working capital efficiency variables include: days receivables (ln), days inventory (ln), days payable (ln) and cash cycle (ln). The solvency variables include: leverage ratio and total facilities ratio. The profitability ratios include gross profit margin and net profit margin. The qualitative variables include: the geographic locations, the legal structure of the entity, the business sectors, the audit status, the customer concentration status and the supplier concentration status. Some of these variables are converted into dummy variables for easy coding using STATA software.

Based on the interpretation of the results in Table 8, the average equity and revenue of non-defaulted entities are higher than those of defaulted entities since non-defaulted entities tend to be more mature and have a higher size of equity and revenue compared to defaulted entities. In the literature, equity as a stand-alone value representing the size of the firm has not been used singularly. Rather, it has been used as the ratio, such as Debt / Equity Variable that appears in Altman and Sabato's (2007) study. Revenue representing size is used by Grunert and Norden (2012) in a study that includes U.S. and German firms. On the other hand, the cost of goods sold by the defaulted entities have a higher average number than the non-defaulted firms. Moreover, the average age of non-defaulted entities is longer than the average age of defaulted entities as a result of the maturity factor.

The days receivables ratio concerns the entity's ability to collect its sales on credit because a higher number of days can lead to a greater probability of the entity's inability to collect its cash from the market and hence default. The defaulted entities have average days receivables that are higher or longer than entities that are non-defaulting. Similarly, defaulting firms tend to be slow in product sales turnover and hence experience a build-up in inventory. This can be measured by the days inventory ratio where defaulted firms have an average days inventory that is higher than the ratio of the non-defaulted firms. Nevertheless, non-defaulted entities tend to enjoy good relationships and support from suppliers when this can be tested by days payables. Non-defaulted entities have an average days payable ratio that is higher than the ratio of defaulted firms. None of days receivables, days inventory and days payables have been used in their pure forms throughout the literature of default prediction. They have been used, instead, as part of the working capital variable, which is a general variable for measuring efficiency (Altman, 1968; Altman, 2005). This research model is unique in using such detailed variables.

A sophisticated ratio that can be used to measure the efficiency of the working capital of the entity in almost all business segments is the cash cycle or cash conversion cycle (Table 8). Unlike defaulted entities, non-defaulted entities tend to have a short cash cycle as a result of their business efficiency and ability to convert stock or raw materials into finished goods, collect their sales and finally pay their suppliers. As mentioned, none of the related literature has previously used the cash conversion cycle as one of the variables for building a credit risk model based on logistic regression.

In general, the defaulted entities are highly leveraged compared to non-defaulted entities, which expose them to a higher probability of default. The profitability measures of the non-defaulted entities have higher than average results than the numbers of the defaulted entities. Similarly, total facilities ratio, which is another type of leverage measure, has a mean that is high for defaulted entities compared to non-defaulted entities.

This study also employs gross profit margin and net profit margin (see Table 8) similar to Altman et al. (2005), which uses the same variables in different forms.

Table 8. Summary statistics on firm characteristics

Variables	Mean All	Median All	Std. Dev.	Mean Defaulted Firms (D)	Mean Non-Def. Firms (ND)	D-ND	Min	Max	t-Stat
Equity Value (Mil)	25.26	18.40	22.68	15.40	25.76	-10.36***	-5.94	239.14	-11.98
Revenue (Mil)	28.54	24.39	19.80	20.95	28.93	-7.98***	1.77	185.22	-10.55
COGS (Mil)	11.30	9.45	8.19	19.18	10.88	8.29***	0.27	90.79	27.00
Age	15.02	15.00	4.33	11.33	15.21	-3.87 ***	2.00	24.00	-23.73
Days Receivable	43.40	38.77	24.30	57.90	42.63	15.23***	3.03	233.16	16.46
Days Inventory	62.01	49.73	64.86	88.60	60.70	27.89***	0.76	1044.05	11.24
Days Payable	37.00	29.09	30.93	25.15	37.60	-12.50***	2.27	628.64	-10.52
Cash Cycle	68.40	62.48	63.86	121.30	65.70	55.60***	-519.59	1005.12	23.10
Leverage Ratio	0.16	0.11	1.19	0.40	0.15	0.21***	-40.57	127.10	4.54
Total Facilities Ratio	0.09	0.08	0.05	0.13	0.09	0.04***	0.01	0.40	20.68
Gross Profit Margin	0.54	0.58	0.27	-0.04	0.56	-0.60***	-1.22	0.98	-65.44
Net Profit Margin	0.20	0.19	0.11	-0.01	0.21	-0.21***	-0.57	0.48	-55.60

Notes: This table derives from STATA SE software version 12.0. The statistical method is a classical test of hypotheses using a two-sample mean comparison test. Significance (i.e. high t value) means that the difference between defaulted and non-defaulted firms for any given variable is statistically different from zero. In other words, firms under these two categories do have different characteristics. The table also outlines the minimum and maximum data for each variable in order to check outliers. *** means 1% significance level; ** means 5% significance level; * means 10% significance level

Based on the t-test of these 12 measures, all the variables are significant at a 1% confidence level since the t-test has a value higher than 2.61. The significance of each variable is marked besides the difference in the means between each variable's two categories: defaulted and non-defaulted entities. The results of this dissertation compare favourably to the literature. Altman and Sabato (2007) have discovered profitability (net profit) as a statistically significant variable in determining the non-performance (default) level of a firm. They suggest that bankruptcy modelling should be done separately for

SMEs and large corporations. Moreover, facility size increases the default probability for SMEs (Featherstone et al., 2006).

In order to ensure that there are no existing outliers in the sample portfolio, Table 8 shows the minimum and maximum data for each variable. Based on Table 8, the minimum equity value is SR 5.94 million with a negative sign. The negative sign is the result of the fact that some entities have encountered losses over time and their equity has been recorded as negative based on their un-audited financial statements. Similarly, their leverage ratio (total liabilities / total equity) has been reported with a negative value where the minimum leverage ratio is -40.57.

The minimum cash cycle in the sample portfolio is -519.59. This is also normal since some entities depend on their funding for suppliers' payables, though, in some cases, there has been mismanagement of funds that led to payables being far greater than receivables and inventory. Cash cycle is calculated as follows: Days Receivables + Days Inventory – Days Payables. Further details on the definition of cash cycles are provided in the variables definitions section.

After the description of the 12 non-dummy variables shown in Table 8, I filter down these variables using the principal component analysis method, as explained in the methodology chapter. Next, I apply logistic regression method on the sample data and analyze the output in the next chapter. I divide the data into two batches to ensure that the default prediction model is well presented: 73% of the data are in the sample to estimate the coefficients of the model and 27% of them are out-of-sample to validate the model. Following the literature, I use annual financial statements since small firms do not have the ability to produce quarter statements (Behr and Guttler, 2007).

5. METHODOLOGY

In this chapter, I cover the several types of statistical methodologies undertaken within the research. The empirical work includes the application of principal component analysis (PCA), logistic regression, ROC analysis and a loan pricing model.

5.1 The PCA Analysis

Principal component analysis (PCA) is an orthogonal method that converts data from multicollinear status to independent data status or non-collinear variables. The resulting output of these variables is always less than the number of input variables. For example, if one conducts principal component analysis procedure for 10 variables, the output number is always smaller than the 10 input variables (Jolliffee, 2002). PCA depends on the degree of correlation among the input data.

This method was introduced in 1901 by Karl Pearson in the field of mechanical engineering (Lins, Servaes and Tufano, 2010). Later on, PCA was upgraded by Hotelling in the 1930s (Lastovicka, 1992). It is also used as a technique in heuristic data analysis and projections models. PCA produces segment scores relating to a specific information point that corresponds to vertical and horizontal labels. PCA is the most straightforward of the genuine eigenvector-based multivariate examinations. It assumes a vital part in today’s business, as it is a basic yet capable method for extricating imperative data from conceivably fragmented informational collections. The result for PCA depends on an essential property of eigenvector deterioration (Lastovicka, 1992).

The objective of using principal component analysis is to avoid multicollinearity and increase the accuracy of the results when applying the logistic regression models. In line with the literature, I apply all the data except the dummy variables. The variables in the PCA analysis are those related to the in-sample period covering the first eight years of the sample portfolio from 2001 to 2008. I apply the PCA analysis using Stata. Besides the dummy variables, these variables are used in the logistic regression model discussed in the next section.

5.2 The Logistic Regression Model

Logistic regression is a regression model where the dependent variable Y can take the binary value of either zero or one. In my study, zero represents non-defaulted firms and one represents defaulted firms. Logistic regression can be binomial, ordinal, or multinomial. The results can be “success” versus “fail” or “current” versus “default,” etc. (Baxter, 2009).

The following is the logistic regression model equation where: Y = 1 if the firm has defaulted and Y = 0 if otherwise (Wooldridge, 2011):

Equation 2: Logistic Regression

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 \ldots.$$

From the resulting regression, it is possible to identify the significant variables to determine the probability of default as presented in the results chapter. The above equation that Ohlson (1980) supplies derives from logistic regression. Unlike linear regression, which assumes a continuous dependent variable, logistic regression operates with discontinuous independent variables. The assumption holds that the dependent variable Y has a linear dependence on the independent variables.

The original form of Ohlson’s model was developed in 1980 when he pioneered the logistic model for predicting defaults. He has used data from the 1970s and 1980s using 2,163 samples, larger than this sample portfolio (Ohlson, 1980). The goal of his study is to find appropriate variables that indicate bankruptcy.

Logistic regression is commonly used in the SMEs credit and default literature. I follow Cowling and Mitchell (2003) and Grunert and Norden (2012) in utilizing logistic models to estimate the loan default probability of the Saudi SMEs bank portfolio. In line with their methodologies, potential defaults are estimated through a set of financial ratios. For the case of SMEs default prediction, Altman and Sabato (2007) strongly suggest the application of a logistic model instead of multiple discriminant analysis (MDA) because of its strength in contrast to the violation of assumptions that occurs with MDA. This is the reason for using the logistic model in my research. Furthermore, a logistic regression application does not need the multivariate normal assumption of discriminant analysis (Frydman et al., 1985).

5.3 The ROC Analysis

The receiver operating characteristic (ROC) is a typical approach for testing the performance of the rating model. The ROC is built by plotting the combined recurrence of non-default entities on the x-axis against the aggregate of default cases on the y-axis. A perfect rating system would run vertically from (0,0) to (0,1) and on a level plane from (0,1) to (1,1) (Fawcett, 2006).

Receiver operating characteristics (ROC) graphs are useful for organizing classifiers and visualizing their performance; they are widely used in medical decision-making. The ROC curve is used to measure the effectiveness of the risk prediction model. In corporate finance, the ROC curve is used to estimate the effectiveness of the area under the curve. These can be based on the Mann–Whitney statistic, kernel smoothing, normal assumptions and empirical transformations to normality (Faraggi and Reiser, 2002). ROC curve analysis is also used to determine the correlation between bankruptcy modelling and credit granting. It is valid in relationship lending that exercises judgment calls yielding higher returns for lenders (Stein, 2005). This method is also applied in estimating the financial gains associated with bankruptcy models covered under the ROC curve (Blöchlinger and Leippold, 2006).

The area under the curve (AUC) is a numerical measure of the zone under the ROC curve. For a perfect rating model, the AUC ought to be 1 and for a non-perfect model, it would be 0.5 (Faraggi and Reiser, 2002). AUC is firmly identified with the Mann–Whitney U that tests whether positives are positioned higher than negatives. It is additionally proportional to the Wilcoxon trial of positions (Faraggi and Reiser, 2002). The ROC tool gives instruments the ability to choose potentially ideal models and to dispose of problematic ones freely from—and preceding, determining—the cost setting or the class dispersion. The ROC curve was first created by electrical specialists and radar engineers amid World War II for distinguishing enemy protests in combat zones. Later, it was associated with psychology research to represent perceptual identification. The ROC curve from that point forward has been utilized as a part of prescription, radiology, biometrics and different zones and is progressively utilized as a part of data modelling (Schweiger, 1958).

5.4 The Loan Pricing Model: Pricing Credit Risk

As part of the methodologies used in this project and in order to have meaningful results, I use a loan-pricing model similar to Bauer and Agarwal (2014) to derive the credit spread for the SMEs classified in each of the 10 portfolios:

$$\mathrm{R}_i = \frac{p_i(Y = 1)}{p_i(Y = 0)} LGD + k$$

Where R_i is the credit spread for portfolio i, $p_i(Y = 1)$ is the probability of default for portfolio i; $p_i(Y = 0)$ is the probability of non-default for portfolio I; LGD is the loss in loan value given default; and k is the credit spread for the highest quality loan.

The bank rejects all firms with probabilities that fall in the top 10% (highest probability of default) while offering credit to all others at a credit spread it derives using the above model. The reason for rejecting the top 10% (or top 5% in practice) of firms is because, from a lender's perspective, the cost of granting credit to a firm that fails subsequently is much higher than the cost of refusing credit to a firm that does not fail. As a result, it would be less costly for the bank to reject credit to firms with the highest probability of default (Dietsch and Petey, 2002; Stein, 2005; Blöchlinger and Leippold, 2006).

The essential factors in debt pricing are the term structure of risk-free rates and the default risk of the borrower. Many models have used leverage to determine the default risk after Merton (1974). The pricing of loans is spread over the cost of funds of banks. Credit evaluation concentrates diverse arrangements of logical factors, taking into account the interest rate. In general, SMEs are less sensitive to loan pricing due to lack of financing. Most SMEs tend to accept higher pricing and sometimes, the owners of these SMEs use several funding sources such as credit cards. SMEs are vulnerable to changes in pricing (Walker, 2010).

Berger and Udell's (1990) study on a portfolio of loans reveals that the pricing of loans is based on a margin that is added to an interbank lending rate. The study has a high confidence level at 5% and indicates that there are factors that affect loan pricing decisions. These are the natural logarithm of the loan amount, the tenor, the security provided by the borrower, the type of facility as a non-revolving or committed facility and the type of commercial paper supporting the loan. Other factors include the cross-border boundaries in which the loan is extended and whether it is a local bank or foreign bank. The type of financing affects the loan pricing in cases when it has bilateral or syndicated financing. The cost of fund benchmark is also a major determinant for loan pricing (Berger and Udell, 1990).

Similarly, another high confidence study (Booth, 1992) at 5%, demonstrates that there are other factors affecting loan pricing. These are the logarithm of revenues, collateral provided by the borrower, the amount of financing and the availability of commitment fees paid by the borrower. Other factors include the terms in which the financing is extended (as committed financing or uncommitted financing). More determinants include the type of financing such as working capital, CapEx financing, or acquisition finance. The completion and the availability of similar borrowers in the industry has an effect on the pricing of debt. The legal structure of the ownership and corporate governance influence the pricing as well. The credit rating, in general, is the determining factor of the loan pricing (Booth, 1992).

Furthermore, Peterson and Rajan's (1994) study of a bank's portfolio shows that there are several determinants for banks to price loans extended to customers. These are:

- The rate at which the loan is extended (floating or fixed).
- The client's historical performance and revenue growth.
- The risk-free rate in which the loan is priced.
- The spread between the sub-investment-grade rating and risk-free rate.
- The number of years the entity has been running.
- The entity's gross profit/assets.
- The debt service coverage of the client.
- The risk rating of clients.
- The availability of financing from other lenders.

Berger and Udell (1995) utilize a similar dataset even though it is designed to investigate the spreads over risk-free rates. They reveal 22 factors affecting loan pricing at. They show that the most important factors determining pricing are the history of default and the length of the association between the client and bank (Berger and Udell, 1995).

There are several loan pricing methodologies. One of the most well-known methodologies is the risk-adjusted return on capital (RAROC). RAROC is used by banks in pricing loans based on the economic capital against the risk rating of the borrower. The idea was created by Investors Trust and its main creator Dan Borge in the late 1970s (Diebold, Doherty and Herring, 2008). The following is the formula for calculating RAROC:

RAROC = Expected Return / Monetary Capital

or,

RAROC = Expected Return / Value at Risk (Prokopczuk et al., 2007).

Value at risk takes into consideration the different types of risk including credit, operational, liquidity and other economic risks.

Economic capital is the capital needed to sustain credit default. RAROC is one of the pricing approaches Basel III recommends (BCBS, 2010). There are some disadvantages in using RAROC. The most common disadvantage is the opportunity cost as a result of net lending money. For example, in some cases, banks refuse to lend to certain clients because the calculated RAROC for the client, based on this risk rating, is lower than the benchmark. The client at the same time refuses to take the loan because of pricing issues. In this case, the bank will leave the loan in the balance sheet at a risk-free rate for quite some time, during which the bank can incur opportunity cost as a result of lending to this client. In these cases, the bank has to manage the liquidity and decide on the optimal investment/lending mix in order to maximize the return on equity, risking an adjusted return on capital (RAROC) (Dermine, 1998). In order to simplify the research, I am using a pricing method based on Bauer and Agarwal (2014), which offers a useful balance between the academic literature and the practical aspect of my research since I do not have to include the several cost components used in RAROC.

6. EMPIRICAL RESULTS

This chapter conveys the results of the empirical project. In the chapter, I first review the principal component analysis (PCA), which filters down the variables that are used in the statistical model. After that, I use the chosen variables to perform logistic regression analysis for the portfolio data between 2001-2008 in order to predict the defaults for the three years between 2009-2011. I present a portfolio plotting for the same model., Next, I develop a more accurate model using the portfolio data from 2003-2010 in order to project the default rates for the year 2011. I also graph the out-of-sample prediction for the portfolios. Afterwards, I show out-of-sample classification accuracy at cut-offs of 5%, 10%, 15%, 20% and 25%, respectively; and plot the receiver operating characteristics (ROC) curve. Finally, I conduct credit risk pricing for SMEs similar to Bauer and Agarwal (2014).

6.1 Principal Component Analysis

In this section, I apply the principal component analysis (PCA) method to this sample. The principal component analysis recommends the use of revenues (mil), age, days inventory, days payable, leverage ratio, gross profit margin, least collinear variables and highly recommended variables to apply for the logistic binary model as shown in Table 9, where the filtered variables are highlighted. Revenue (Mil), representing the size of the firm, is also filtered through the PCA. The PCA analysis also chooses the age variable, in line with Grunert and Norden (2012), who use age as one of the soft skills in their study.

On the other hand, the PCA did not select equity value (Mil) and COGS (Mil), as revenue has been chosen to represent size. Based on the literature, this compares favorably with Grunert and Norden (2012) who study the use of soft skills on a sample of U.S. and German entities. Their variables include the natural logarithms of the entity revenue representing the size of the entity (Grunert and Norden, 2012). I was surprised not to see days receivables and cash cycle in the filter. As an ex-credit officer, I used to look at these variables carefully when I conducted credit analysis on my clients. Days receivables and cash cycle can be valid indicators of the health of a firm's receivables collection. One of the reasons that days receivables and cash cycle are not filtered is because of the fact that these SMEs do not depend heavily on credit sales, unlike larger corporations.

Days inventory and days payable are chosen as working capital indicators variables in my study. This is because my portfolio consists of a good number of trading and manufacturing entities. Banks usually lend to clients at a certain tenor that matches the cash conversion cycle of clients. In contrast, Altman (1968) uses working capital/total assets, which is the closest working capital variable that includes days receivables and days payables components.

Leverage is filtered through PCA; similarly, Altman (1968), Altman and Sabato (2007), Merton (1974) and Taffler (1983) use leverage in several forms. Gross margin is set against net margin. As mentioned, gross margin reflects the efficiency of the firm whereas net margin reflects bottom lime profitability. Gross profit is used in several versions in the literature (Altman, 2005).

Table 9. Principal component analysis (PCA)

Variables	Gross Profit Margin	Days Inventory	Revenue (Mil)	Leverage Ratio	Days Payable	Age
Equity Value (Mil)	0.3587	-0.0413	0.4087	-0.0434	0.2457	0.0552
Revenue (Mil)	0.3198	-0.1865	0.4945	-0.0065	0.1762	-0.0328
COGS (Mil)	-0.084	-0.4002	0.4885	0.0077	0.0742	-0.1578
Age	0.3254	-0.0684	-0.0173	-0.0571	-0.0325	0.6123
Days Receivable	-0.3552	0.1854	0.089	-0.1279	0.4878	0.4084
Days Inventory	0.0994	0.5173	0.2716	0.0542	-0.2188	-0.3062
Days Payable	0.1925	0.2767	-0.1927	0.0369	0.6491	-0.4456
Cash Cycle	-0.1274	0.4619	0.403	-0.0114	-0.3511	0.0602
Leverage Ratio	-0.0506	0.0062	0.0402	0.9845	0.0744	0.1413
Total Facilities Ratio	-0.3681	0.3023	0.2112	-0.0681	0.257	0.2301
Gross Profit Margin	0.4208	0.2427	-0.1058	0.0036	-0.0043	0.1497
Net Profit Margin	0.3895	0.2376	-0.1045	0.002	-0.0054	0.195

Notes: Principal component analysis (PCA) is a statistical technique used for data reduction. The leading eigenvectors from the eigen decomposition of the correlation or covariance matrix of the variables describe a series of uncorrelated linear combinations of the variables that contain most of the variance. The first column on the left includes all the non-dummy variables. The highlighted variables are those non-collinear variables that are used to name the rest of the columns. The remaining highlighted cells in columns 1-6 contain highlighted data. The highlighted data in each column represent the highest data cell in each column that corresponds both vertically and horizontally to the non-collinear variables. The six variables selected by the PCA analysis cumulatively account for 90.7% of the total variability of the data.
This table was created through STATA SE version 12.0 by using multivariate analysis-factor and component analysis (PCA).

The six variables selected by the PCA analysis cumulatively account for 90.7% of the total variability of the data. The next section uses the PCA filtered variables to construct the model, analyzing eight years of data (2001-2008).

6.2 Modelling Credit Risk: Logistic Regressions (2001-2008)

In this section, I apply the logistic regression model on the six selected quantitative variables filtered by the PCA method and add all the eight dummy variables: Eastern (1/0), Western (1/0), sole proprietorship (1/0), contracting (1/0), trading (1/0), audited (1/0), concentrated customer (1/0), concentrated supplier (1/0)). See Table 7 for the definitions of the dummy variables. After running the regression, I obtain statistical results for model one as shown in Table 10. Logistic model one reveals five significant variables with a 1% confidence level. Logistic model one has a pseudo R^2 of 0.791. These significant variables are gross profit margin, days inventory (ln), eastern (1/0), contracting (1/0) and concentrated suppliers (1/0) as highlighted in Table 10.

Table 10. Logistic regressions for 2001-2008

Variable	Model 1	Model 2
Gross Profit Margin	-19.28***	-19.17***
	(-18.70)	(-19.69)
Days Inventory (ln)	0.46***	0.41***
	(2.85)	(2.66)
Revenue (ln)	0.19	
	(1.27)	
Leverage Ratio	-0.17	
	(-1.52)	
Days Payable (ln)	0.05	
	(0.25)	
Age (ln)	-0.19	
	(-0.75)	
Eastern (1/0)	0.43*	0.44**
	(1.79)	(2.24)
Western (1/0)	-0.06	
	(-0.25)	
Sole Proprietorship (1/0)	-0.04	
	(-0.22)	
Contracting (1/0)	0.93**	0.78**
	(2.22)	(2.08)
Trading (1/0)	0.17	
	(0.76)	
Audited (1/0)	-0.18	
	(-0.94)	
Concentrated Customer (1/0)	0.05	
	(0.28)	
Concentrated Supplier (1/0)	1.85***	1.85***
	(6.78)	(6.83)
Constant	-6.46	-3.42
	(-2.19)	(-5.70)
Observations	9583	9583
X^2	2914.08	2908.70
Pseudo R^2	0.791	0.789

Notes: t-statistics are in parenthesis; *** means 1% significance level; ** means 5% significance level; * means 10% significance level. The table presents the results of two logistic regression models using the sample SMEs portfolio of the Saudi bank. The logistic regression is based on the in-sample historical data of entities for the period from 2001-2008. The input variables are the PCA filtered variables including all the dummy variables. The dependent value (Y) takes a binary value where Y = 1 if the entity defaults and Y = 0 if the entity does not default in a given physical year. The first model variables are: gross profit margin, which is gross profit divided by sales; days inventory (ln), which is the natural logarithm of inventory / cost of goods sold times 360; revenue (ln) is the natural logarithm of revenues; leverage ratio equals total liabilities divided by equity; days payable (ln) is the natural logarithm of payables divided by the cost of goods sold times 360; age (ln) is the natural logarithm of the number of years since the entity was established. The remaining are the dummy variables: Eastern (1/0) and Western (1/0) are geographic locations. Sole proprietorship (1/0) refers to the legal structure; contracting (1/0) and trading (1/0) are business sectors; audited (1/0) is the status of an audit; concentrated customer (1/0) and concentrated supplier (1/0) are the risk of the entity having few customers and/or suppliers. Model two uses only the significant variables that resulted from model once. t-statistics are illustrated between brackets.

After that, I use the five significant variables that resulted from model one to create a model two logistic regression, which shows a pseudo R^2 of 0.789 as presented in Table 10. The two models indicate that gross profit margin is a significant variable with a negative sign since this ratio negatively correlates with the entity's bankruptcy, i.e. the higher the gross profit margin of the entity the less probability of default and vice versa. On the other hand, days inventory (ln) or the natural logarithm of days inventory positively relates to the entity's default. This is clear as the longer the entity stocks its inventory, the higher the probability of default since it will not be able to convert its inventory into cash and pay its obligations.

The model indicates that some qualitative variables are significant with positive coefficients such as the location and business sector. For instance, firms that are located in the eastern region and/or involved in the contracting sector are statistically significant and tend to have a higher probability of default with 0.43 and 0.93 coefficients. Lastly, the model reveals a significant qualitative variable, namely supplier concentration. This is logical if an entity has few suppliers, which exposes the entity to high risk and competitive disadvantage when it comes to securing its supplies. In turn, that can lead to higher supplies pricing, delays in processing transactions and hence, exposure to default in paying obligations to creditors.

The five variables that are statistically significant move at specific increments because of their descriptive nature, which falls in line with the descriptive statistic reports discussed earlier. The significance of profitability and efficiency variables to predict SMEs probability of default is in line with the previous research by Edmister (1972) and

Altman and Sabato (2007) although the number of significant variables is fewer than theirs and in other studies. Comparing these variables with the literature, Ohlson (1980) has the log (total assets / GNP price level index) representing the size index; the financial structure represented by total liabilities / total assets, performance (net income / total assets) and current liquidity (current liabilities / current assets). Ohlson (1980) has produced four models with R-square: 0.84, 0.797, 0.719 and 0.84 in respectively.

Similarly, Behr and Guttler (2007) have found 14 significant variables out of 18 variables in their model conducted on German firms in 2007. Their model has a low R-square at 0.187. Similar to this model, location and business sector variables are significant. The model for this dissertation has Eastern (1/0) and contracting (1/0) as significant dummy variables while Behr's model has Western Germany, retail/wholesale and manufacturing as significant variables (Behr and Guttler, 2007).

Moreover, Altman and Sabato's (2007) study results in the R-square at 0.75 based on the unlogged model and 0.8722 based on the logged model. Their study reveals five significant ratios that are considered the best at that time for estimating SMEs default prediction model. These variables are:

+ *Log (1 – EBITDA / Total Assets)*

- *Log (Short Term Debt / Equity Book Value)*

+ *Log (1 – Retained Earnings / Total Assets)*

+ *Log (Cash / Total Assets)*

+ *Log (EBITDA / Interest Expenses)*

Using the significant variables depicted in model two applied on the in-sample eight years of data from 2001 until 2008 (see Table 10), I can apply the following logistic regression equation for the out-of-sample portfolio entities for the last three years from 2009 until 2011:

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5$$

where: Y = is the probability of default

Based on the results I substitute the values for a, X's and b's as follows:

<u>*Equation 3: Logistic Regression for 2009-2011*</u>

Y = -3.42 -19.17 Gross Profit Margin + 0.41 (Days Inventory (ln) + 0.44 (Eastern (1/0)) + 0.78 (Contracting (1/0) + 1.85 (Concentrated Supplier (1/0))

Next, I calculate Y for each entity for the sample portfolio for the last three years from 2009 until 2011. Then, I rank Y or the resulting dependent variables from the highest to lowest value in order to compare them against their actual performance, where Y = 1 for defaulted firms and 0 for non-defaulted firms. Finally, I graph the classification accuracy of the sample portfolio (2009-2011) in the next section using portfolio approach.

6.3 Classification Accuracy for Years 2009-2011: Portfolio Approach

In this section, I present a graph that shows the bankruptcy probability percentiles based on the classification accuracy for the model portfolio, predicting defaults for the years 2009-2011 based on the model from years 2001-2008 (see Figure 5). In considering the application of Altman and Sabato's (2007) and Ohlson's 1980) models when it comes to bankruptcy prediction, U.S. studies have been utilized less frequently in recent years compared to times when they were originally used. This is clear with respect to the use of variables in statistical models (Begley et al., 1996). The literature exhibits the importance of conducting international surveys to validate the accuracy of default prediction models (Altman and Narayanan, 1997). My purpose is to validate the accuracy of the constructed model.

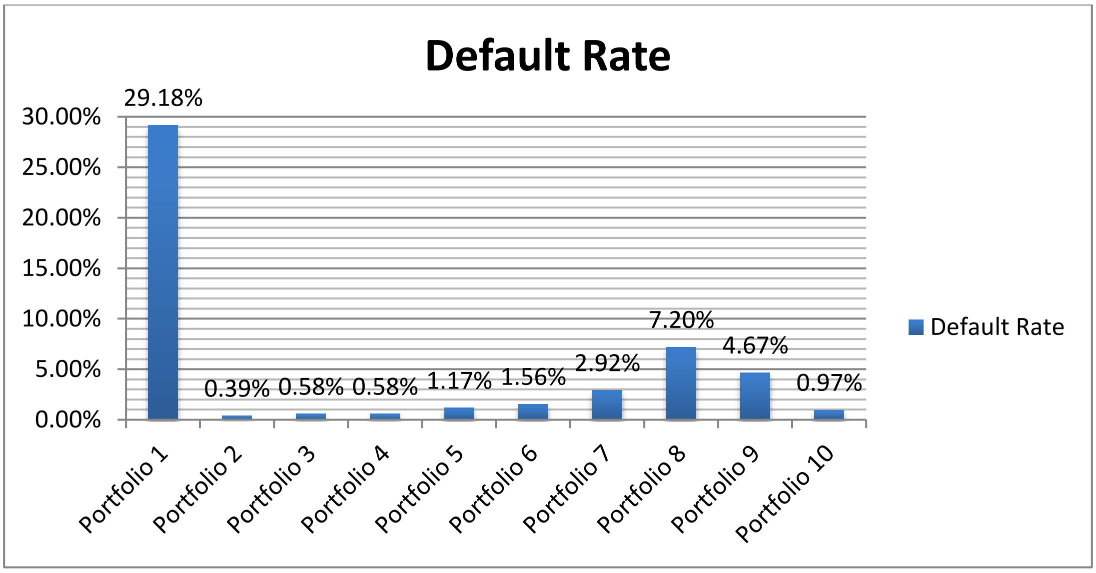


Figure 5: Out-of-sample prediction by decile portfolios (2009-2011)

Notes: The figure is prepared by ranking Y for the last three years (2009-2011), classifying output from the highest to lowest value and dividing the portfolio equally into 10 portfolios, where each portfolio has 10% of the data observations. After that, I count the defaulted observations under each portfolio and calculate the default rate. As can be seen, most of the defaults fall in portfolio number 1 which indicates that this logistic regression model has a high predictability power.

Based on Figure 5, most of the defaults have fallen in portfolio 1, indicating that the resulting logistic regression model has high predictability. Nevertheless, it is odd to see that the bankruptcy probability percentiles shown in the figure are heterogeneous, where the distribution of the default rate should be descending from portfolio 1 down to portfolio 10. The default rate for portfolios 7-9 increases, which indicates that we have no control over market conditions. This is not surprising and in fact analogous to Mensah's finding. There may be some unexpected market conditions that led some firms to default in the period 2009-2011. Statistical models can be exposed to a certain degree of error depending on many factors related to the economic dynamics surrounding the firms and the industrial segment in which the firms operate. Results can be inconsistent (Mensah, 1984). Furthermore, Balcaen and Ooghe (2006) identify some issues with the said statistical techniques. They claim that the techniques are highly influenced by the collinearly patterns of variables and the non-consistency over time influenced by changing economic conditions (Balcaen and Ooghe, 2006).

These market conditions can cause economic and political instabilities. Indeed, there were economic and political crises during this period. Oil prices were volatile between 2009-2011; the Arab world witnessed the emergence of the Arab Spring and the revolutions that shook up the region especially in Libya, Egypt and Syria. These among other unknown factors could be the unexpected reasons why this model works within the said period. The Saudi economy was not isolated from what happened in the region. Using an alterative sorting for the portfolios would lead to a smooth default rate. These historical factors led me to generate an updated model that uses alternative panel data for the eight years from 2003 to 2010, in contrast to the previous period of 2001-2009. The model in the next section aims to predict 2011 as a single year. The major difference between the updated model and the previous model is that it is intended to predict one year instead of three years.

In the next section, I apply the same method reviewed previously on different data sets between 2003-2010 in order to predict the expected defaults of the year 2011.

6.4 Modelling Credit Risk: Logistic Regressions (2003-2010)

Following the approach applied in model one and model two, in this section, I apply the logistic regression method using the same selected quantitative variables filtered by the PCA method including the eight dummy variables. The results are shown in Table 11. Unlike the previous model, the new model reveals nine significant variables. Model one has a pseudo R^2 of 0.63.

Table 11. Logistic regression for 2003-2010

Variable	Model 1	Model 2
Gross Profit Margin	-10.90***	-10.84***
	(-25.59)	(-25.66)
Days Inventory (ln)	1.35***	1.35***
	(12.02)	(12.07)
Revenue (ln)	0.53***	0.52***
	(5.00)	(4.95)
Leverage Ratio	0.00	
	(-0.25)	
Days Payable (ln)	0.40***	0.38***
	(2.91)	(2.81)
Age (ln)	-0.04**	-0.04**
	(-2.40)	(-2.36)
Eastern (1/0)	0.08	
	(0.51)	
Western (1/0)	-0.26	
	(-1.59)	
Sole Proprietorship (1/0)	-0.02	
	(-0.13)	
Contracting (1/0)	2.62***	2.68***
	(9.54)	(9.79)
Trading (1/0)	0.53***	0.55***
	(3.57)	(3.69)
Audited (1/0)	-0.23*	-0.23*
	(-1.78)	(-1.79)
Concentrated Customer (1/0)	-0.14	
	(-1.08)	
Concentrated Supplier (1/0)	1.72***	1.73***
	(10.33)	(10.39)
Constant	-15.98***	-15.99***
	(-7.94)	(-8.00)
Observations	11797	11797
X^2	2997.65	2991.08
Pseudo R^2	0.630	0.628

Notes: t-statistics are in parenthesis; *** means 1% significance level; ** means 5% significance level; * means 10% significance level.

The table presents the results of two logistic regression models using the sample SMEs portfolio of the Saudi bank. The logistic regression is based on the in-sample historical data of entities for the period of 2003-2010. The input variables are the PCA filtered variables including all the dummy variables. The dependent value (Y) takes the binary value, where Y = 1 if the entity defaults and Y = 0 if the entity does not default in a given physical year. The first model variables are: gross profit margin, which is gross profit divided by sales; days inventory (ln) is the natural logarithm of inventory / cost of goods sold times 360. Revenue (ln) is the natural logarithm of revenues; leverage ratio equals total liabilities divided by equity; days payable (ln) is the natural logarithm of payables divided by cost of goods sold times 360; age (ln) is the natural logarithm of the number of years since the entity was established. The remaining are the dummy variables: Eastern (1/0), Western (1/0) are geographic locations. Sole proprietorship (1/0) is legal structure; contracting (1/0), trading (1/0) are business sectors; audited (1/0) is the status of audit; concentrated customer (1/0) and concentrated supplier (1/0) are the risks of the entity having too few customers and/or suppliers to deal with. Model two uses only the significant variables that result from model one. T-statistics are illustrated between brackets.

Using the nine significant variables to create model two, logistic regression reveals the pseudo R^2 of 0.628 as presented in Table 11. The two models indicate that gross profit margin is a significant variable with a negative coefficient as the profitability represented by gross margin has a negative relationship with the expected default. In line with the previous model, days inventory is considered significant because of its positive correlation with bankruptcy. Surprisingly, the size variable represented by revenues (ln) or the naturally logged revenue has positive coefficients at 0.52, which parallels the results of Hillegeist et al. (2004). Days payable is positively correlated to default with 0.38 coefficient. The age variable is negatively correlated with default because the older the firm, the less probability that it might be exposed to default.

Similar to the previous model, some qualitative variables are significant with positive coefficients at 2.68 and 0.55 for business sectors that include contracting and trading. This is in line with Behr and Guttler (2007) who have found 14 significant variables out of 18 variables in their model conducted on German firms in 2007. Their model has a low R-square at 0.187 (Behr and Guttler, 2007). The model reveals a significant qualitative negative variable related to the audit status where firms that produce audited financial statements have a smaller probability of default compared to unaudited ones. Concentrated supplier variable has a negative coefficient in line with the previous model. The intercept came at -15.99. Most of the model two variables are significant with a 1% confidence level.

Next, using the nine significant variables extracted from model two applied on the in-sample eight years data from 2003 until 2010 (see Table 11), one can apply the following logistic regression equation for the out-of-sample portfolio entities for the single year 2011:

Equation 4: Logistic Regression for 2011

Y= -15.99 -10.84 Gross Profit Margin +1.35 Days Inventory (ln)+ 0.52 Revenue (ln) + 0.38 Days Payable -0.04 Age (ln) + 2.68 Contracting (1/0) + 0.55 Trading (1/0) -0.23 Audited (1/0) + 1.73 Concentrated Supplier (1/0)

where: Y = is the probability of default for the year 2011

Again, I calculate Y for each entity for the sample portfolio for the single year 2011. I rank Ys or the resulting dependent variables from the highest to the lowest, in order to compare them against their actual performance, where Y = 1 for defaulted firms and Y =

0 for non-defaulted firms. Next, I check the classification accuracy of the sample portfolio and the decile portfolios (Figure 6) in the following sections.

6.5 Classification Accuracy for Year 2011: Portfolio Approach

In this section, I illustrate the classification accuracy for the year 2011 using 2003-2010 data. As indicated in Figure 6, the last model based on 2003-2010 in-sample portfolio data has better predictability than the previous model, which uses portfolio data based on the in-sample period of 2001-2008. The initial model is influenced by market conditions more than the latest model. Therefore, the model has accurate prediction power as a result of less market disruption. Regardless of how strong a model is, it cannot beat the market and perfectly predict the future, which falls in line with market efficiency theory (Fama, 1998). Figure 6 presents the default rate for each of the decile portfolios in anticipation of assigning the right credit pricing, which is presented in section 6.8.

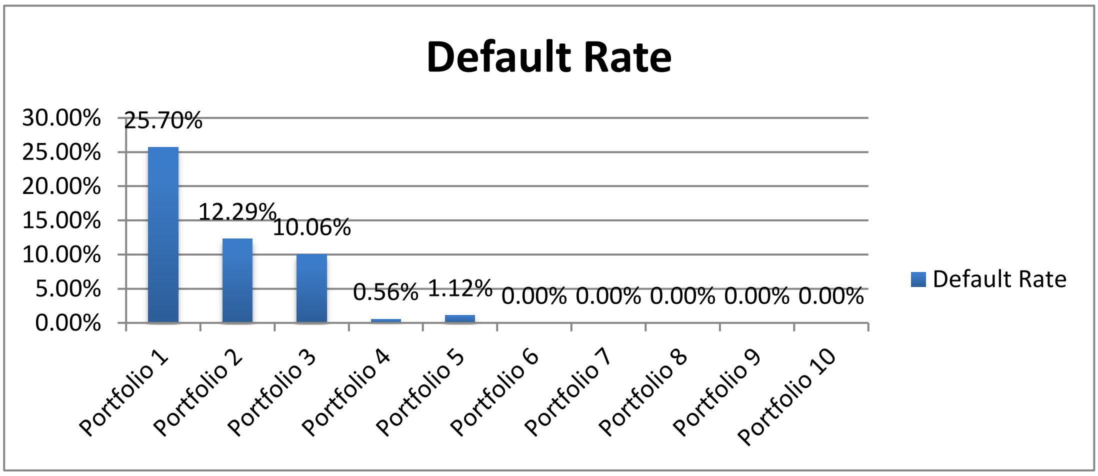


Figure 6: Out-of-sample prediction by decile portfolios (2011)

This figure has been prepared by ranking Ys for the year 2011 data from the highest to lowest and dividing them equally into 10 portfolios, where each portfolio has 10% of the data observations. After that, the defaulted observations under each portfolio are counted and the default rate is calculated. As can be seen, most of the defaults fall in portfolio number 1, then 2 and 3, which indicates that this logistic regression model has a high predictability that is better than the previous model, based on the in-sample year 2001-2008. The next section presents the classification accuracy-cutoffs for the year 2011.

6.6 Classification Accuracy: Cut-offs

In the previous section, I reveal the value of the dependent variables' Ys based on the logit regression model. In this section, I explore the classification accuracy for 2011 at several cut offs: 5%, 10%, 15%, 20% and 25%. I also compare these classification accuracies to the relevant literature.

Based on the default prediction model shown in Table 12, the top 5% of entities with the highest default chances garner a predictive classification accuracy of 44.94% and 97.07% for defaulted entities and non-defaulted entities, respectively. The same table indicates that 49 actual defaults (55.10%) are misclassified as non-defaulted (a type I error). There are 50 entities (2.93%) incorrectly classified as defaults (a type II error). In other words, the model has a high level of accuracy.

Classification accuracy is utilized in logistic regression models as a factual measure of how accurately the model tests the material. Classification accuracy is the degree of genuine outcomes, both genuine positives and genuine negatives, among the aggregate number of cases examined (Metz, 1978). It is a parameter of the test.

In statistics, the classification accuracy of an estimation framework is estimations of an amount's level of accuracy relative to that amount's actual value (Joint Committee for Guides in Metrology, 2012). The level of accuracy of an estimation framework, identified by reproducibility and repeatability, is how much re-tested estimations under unaltered conditions deliver the same results (Taylor, 1997).

Statistical models have different levels of accuracies. They can be tested at different cut-offs. Accuracy is connected to circuitous estimations, that is, qualities acquired by a computational method from watched information.

The measurement of a classification, as shown in this section, contains details about type I errors and type two errors. A type I error is the off-base dismissal of an accurate observation (Masters, 2016). Typically, this kind or error drives one to presume that a gathered impact or relationship exists when it actually does not. Alternatively, one excludes true samples based on the assumption that they are not true. For instance, there could be a number of failed students in an exam who have not failed. In this research context, the type I error that could occur at different levels or percentages of the portfolio is the assumption that a number of defaulted entities within the tested level defaulted even though, in reality, they did not default. On the other hand, a type II error is the acceptance of a sample that is supposed to be false. For example, one can take a portion of the sample result and assume that the entities in the sample are current, but the result reveals the opposite: the sample includes defaulted entities (Masters, 2016).

Table 12. Out-of-sample classification accuracy: Top 5%

Predicted D	**Predicted ND**	**Total Obs.**	**Correct D**
90	1706	1796	40
% Correct D to Total Obs.	**Correct ND**	**Type I Error**	**Type II Error**
2.23%	1657	49	50
% Correct D	**% Correct ND**	**% Type I Error**	**% Type II Error**
44.94%	97.07%	55.10%	2.93%

Notes: Table 12 outlines the out-of-sample classification accuracy for the top 5% observations which have the highest probability of default. The first row shows the number of predicted defaults (D), the number of predicted non-defaults (ND), total number of firms, and the number of correctly predicted defaults, respectively. The second row presents the proportion of correctly predicted defaults to total number of observations, the number of correctly predicted non-defaults (ND), the number of type I errors (i.e., actually defaulted but predicted as non-default), and the number of type II errors (i.e., actually not defaulted but predicted as default), respectively. The third row calculates the accuracy ratios of correctly predicted defaults and correctly predicted non-defaults, and the percentages of type I and type II errors, respectively.

In addition to the previous classification accuracy cutoff, Table 13 presents the classification accuracy for the top 10% of the portfolio. The results reveal a 51.68% predictive accuracy for defaulted entities versus a 92.15% classification accuracy for non-defaulted entities. The type I error (misclassified as non-defaulted) includes 43 actual defaults or 48.31% compared to 134 entities (7.85%), which were incorrectly classified as defaults (type II error).

Table 13. Out-of-sample classification accuracy: Top 10%

Predicted D	**Predicted ND**	**Total Obs.**	**Correct D**
180	1616	1796	46
% Correct D to Total Obs.	**Correct ND**	**Type I Error**	**Type II Error**
2.56%	1573	43	134
% Correct D	**% Correct ND**	**% Type I Error**	**% Type II Error**
51.68%	92.15%	48.31%	7.85%

Notes: Table 13 outlines the out-of-sample classification accuracy for the top 10% observations which have the highest probability of default. The first row shows the number of predicted defaults (D), the number of predicted non-defaults (ND), total number of firms, and the number of correctly predicted defaults, respectively. The second row presents the proportion of correctly predicted defaults to total number of observations, the number of correctly predicted non-defaults (ND), the number of type I errors (i.e., actually defaulted but predicted as non-default), and the number of type II errors (i.e., actually not defaulted but predicted as default), respectively. The third row calculates the accuracy ratios of correctly predicted defaults and correctly predicted non-defaults, and the percentages of type I and type II errors, respectively.

Table 14 represents the out-of-sample 15% classification accuracy. Based on the information, the predictive classification accuracy of the defaulted entities falls at 62.92%, whereas, for non-defaulted entities, the predictive classification accuracy at the top 15% is 87.53%. There are 33 actual defaults representing 37.10% that are misclassified as non-defaulted (type I error). On the other hand, 213 entities (12.5%) are incorrectly classified as defaults, which is the type II error.

Table 14. Out-of-sample classification accuracy: Top 15%

Predicted D 269	**Predicted ND** 1527	**Total Obs.** 1796	**Correct D** 56
% Correct D to Total Obs. 3.12%	**Correct ND** 1494	**Type I Error** 33	**Type II Error** 213
% Correct D 62.92%	**% Correct ND** 87.53%	**% Type I Error** 37.10%	**% Type II Error** 12.50%

Notes: Table 14 outlines the out-of-sample classification accuracy for the top 15% observations which have the highest probability of default. The first row shows the number of predicted defaults (D), the number of predicted non-defaults (ND), total number of firms, and the number of correctly predicted defaults, respectively. The second row presents the proportion of correctly predicted defaults to total number of observations, the number of correctly predicted non-defaults (ND), the number of type I errors (i.e., actually defaulted but predicted as non-default), and the number of type II errors (i.e., actually not defaulted but predicted as default), respectively. The third row calculates the accuracy ratios of correctly predicted defaults and correctly predicted non-defaults, and the percentages of type I and type II errors, respectively.

The out-of-sample classification accuracy for the top 20% has divergent predictions. The classification accuracy of the failed entities is 76.40%. That is lower than the percentage of the non-defaulted entities, which came to 82.95%. There are 21 actual defaults (23.60%) that are misclassified as non-defaulted (type I error), compared to 291 entities (17.05%) that are incorrectly classified as failed entities (type II error). See Table 15 for more details.

Table 15. Out-of-sample classification accuracy: Top 20%

Predicted D 359	**Predicted ND** 1437	**Total Obs.** 1796	**Correct D** 68
% Correct D to Total Obs. 3.79%	**Correct ND** 1416	**Type I Error** 21	**Type II Error** 291
% Correct D 76.40%	**% Correct ND** 82.95%	**% Type I Error** 23.60%	**% Type II Error** 17.05%

Notes: Table 15 outlines the out-of-sample classification accuracy for the top 20% observations which have the highest probability of default. The first row shows the number of predicted defaults (D), the number of predicted non-defaults (ND), total number of firms, and the number of correctly predicted defaults, respectively. The second row presents the proportion of correctly predicted defaults to total number of observations, the number of correctly predicted non-defaults (ND), the number of type I errors (i.e., actually defaulted but predicted as non-default), and the number of type II errors (i.e., actually not defaulted but predicted as default), respectively. The third row calculates the accuracy ratios of correctly predicted defaults and correctly predicted non-defaults, and the percentages of type I and type II errors, respectively.

Finally, the default 25% predictive model with the highest default chances shown in Table 16, leads to a predictive classification accuracy of 87.64% and 78.30% for defaulted entities and non-defaulted entities, respectively. These results differ from Altman and Sabato's (2007) study, which achieves a 30% accuracy level; it fell at 78.41-80.16% for defaulted entities and 75.43-87.22% for non-defaulted entities. Moreover, the same table shows that there are 11 actual defaults; 12.40% are misclassified as non-defaulted (type I error). Against 371 entities, 21.73% are incorrectly classified as defaults (type II error). Comparably, Altman and Sabato (2007) apply two models (logged and unlogged). Their type I error results arrive at the lower levels of 11.76% for the logged model and 21.63% for the unlogged model. Nevertheless, their type II error falls at 27.92% and 29.56% for the logged and unlogged models, respectively (Altman and Sabato, 2007).

Table 16. Out-of-sample classification accuracy: Top 25%

Predicted D	**Predicted ND**	**Total Obs.**	**Correct D**
449	1347	1796	78
% Correct D to Total Obs.	**Correct ND**	**Type I Error**	**Type II Error**
4.34%	1336	11	371
% Correct D	**% Correct ND**	**% Type I Error**	**% Type II Error**
87.64%	78.30%	12.40%	21.73%

Notes: Table 16 outlines the out-of-sample classification accuracy for the top 25% observations which have the highest probability of default. The first row shows the number of predicted defaults (D), the number of predicted non-defaults (ND), total number of firms, and the number of correctly predicted defaults, respectively. The second row presents the proportion of correctly predicted defaults to total number of observations, the number of correctly predicted non-defaults (ND), the number of type I errors (i.e., actually defaulted but predicted as non-default), and the number of type II errors (i.e., actually not defaulted but predicted as default), respectively. The third row calculates the accuracy ratios of correctly predicted defaults and correctly predicted non-defaults, and the percentages of type I and type II errors, respectively.

In this section, I chart the classification accuracy cut-offs for the top 5%, 10%, 15%, 20% and 25% portfolio levels. It is clear from these results that the model's accuracy is high. I also compare the classification accuracies of these cut-offs against the literature (Altman and Sabato, 2007).

6.7 Receiver Operating Characteristics (ROC) Curve

In this section, I plot the receiver operating characteristics (ROC) curve. The ROC curve is used to measure the effectiveness of the risk prediction model. The ROC curve is used in corporate finance to estimate the effectiveness of the area under the curve. This can derive from the Mann–Whitney statistic, kernel smoothing, normal assumptions and empirical transformations to normality (Faraggi and Reiser, 2002). ROC curve analysis is also used to determine the correlation between bankruptcy modelling and credit granting. It is valid in relationship lending, which exercises judgmental calls to yield higher returns for lenders (Stein, 2005). This method also applies to estimating the financial gains associated with applying bankruptcy models covered under the ROC curve (Blöchlinger and Leippold, 2006).

ROC is a typical approach for testing the performance of the rating model. The ROC is built by plotting the combined recurrence of non-default entities on the x-axis against the aggregate of default cases on the y-axis (see Figure 7). A perfect rating system would run vertically from (0,0) to (0,1) and on a level plane from (0,1) to (1,1) (Fawcett, 2006).

The area under the curve (AUC) is the numerical measure of the zone under the ROC curve. For a perfect rating model, the AUC ought to be one and for a non-perfect model, it would be 0.5 (Faraggi and Reiser, 2002).

AUC is firmly identified with the Mann–Whitney U, which tests whether positives are positioned higher than negatives. It is additionally proportional to the Wilcoxon trial of positions (Faraggi and Reiser, 2002). As the ROC curve demonstrates, the area under the curve is 93.3%, which is significantly higher (z stat = 78.7) than the random model (area under the curve = 50%).

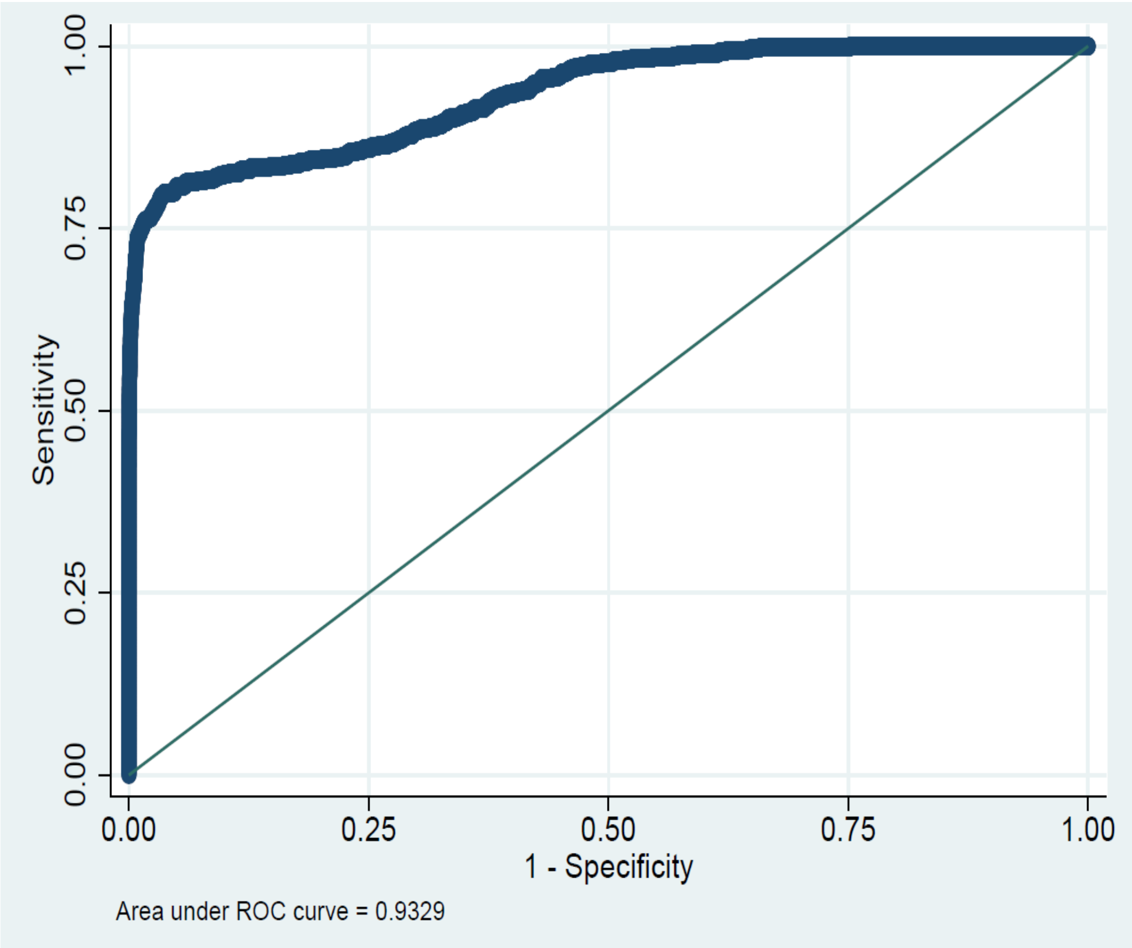


Figure 7: Receiver operating characteristics (ROC) curve: out-of-sample

Notes: Reference variable = Y (the probability of default); Classification variable = Default (1/) [The dummy variable of default]; Z = (0.9329-0.5) / 0.0055 = 78.7 which is highly significant in its difference from the random model.

6.8 Pricing Credit Risk

I use a loan-pricing model similar to Bauer and Agarwal (2014) to derive the credit spread for the SMEs classified in each of the 10 portfolios shown in Figure 6 as follows:

Equation 5: Pricing Credit Risk

$$\mathrm{R}_i = \frac{p_i(Y = 1)}{p_i(Y = 0)} LGD + k$$

Where R_i is the credit spread for portfolio i, $p_i(Y = 1)$ is the probability of default for portfolio I; $p_i(Y = 0)$ is the probability of non-default for portfolio I; LGD is the loss in loan value given for default; and k is the credit spread for the highest quality loan.

The bank rejects all firms with probabilities that fall in the top 10% (highest probability of default) while offering credit to all others at a credit spread derived using the above model. The reason for rejecting the top 10% of firms (or top 5% in practice) is because, from a lender's perspective, the cost of granting credit to a firm that fails subsequently is much higher than the cost of refusing credit to a firm that does not fail. As a result, it would be less costly for the bank to reject credit to firms with the highest probability of default. Table 17 lists the credit spreads that need to be charged for each portfolio.

In Table 17, I use three average spread assumptions. Average spread assumption 1 has the lowest loss given default (LGD) at 45% and a spread of 3%. I have chosen this based on my practical experience in SMEs financing. Average spread assumption 2 has a higher LGD at 50% and a 4% spread. The higher rate is assumed in order to compensate for higher risk. Finally, average spread assumption 3 has the highest LGD at 55% and a 5% spread. Having three assumptions is designed to hypothetically show several pricing ranges associated with certain default buckets.

In general, SMEs are less sensitive to loan pricing due to lack of financing. Al of SMEs tend to accept higher pricing and sometimes the owners of these SMEs use several funding sources such as credit cards. SMEs are sensitive to changes in pricing (Walker, 2010).

Table 17. Average credit spread for SMEs in each default probability portfolio

	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5	Port. 6	Port. 7	Port. 8	Port. 9	Port. 10
Avg. Credit Spread (Assumption 1)	Reject	9.31%	8%	6%	4%	3%	3%	3%	3%	3%
Avg. Credit Spread (Assumption 2)	Reject	11.01%	9.59%	6.97%	4.57%	4.00%	4.00%	4.00%	4.00%	4.00%
Avg. Credit Spread (Assumption 3)	Reject	12.71%	11.15%	8.26%	5.62%	5.00%	5.00%	5.00%	5.00%	5.00%

Notes: First, all SMEs are ranked according to their probability of default, with the top having the highest probability of default and the bottom having the lowest probability of default. Next, the SMEs are sorted into 10 portfolios: Port. 1 includes firms from 0 to 10th percentile, Port. 2 includes firms from 11 to 20th percentile and so on. Assumption 1: LGD = 45.0%, k = 3%; Assumption 2: LGD = 50%, k = 4%; Assumption 3: LGD = 55%, k = 5% (Bauer and Agarwal, 2014)

Based on Table 17, the average credit spreads for SMEs decrease as the risk rating of the borrower or the risk portfolio goes down. The pricing of SMEs depends on the loss given default (LGD) and the credit spread. The LGD refers to the percentage of the exposure at default (EAD); The credit default risk can be mitigated, as mentioned earlier, by taking collateral against a loan as a second way out of exposure payments. In more developed markets for certain financial securities, banks tend to ensure exposures by buying the right credit defaults protections to hedge against credit deteriorations (Altman and Hotchkiss, 2011; Altman et al., 2005; DeYoung et al., 2004).

7. CONCLUSION

Saudi Arabia, a member of the G20 countries, has become a significant force on the stage of the world economy. Saudi Vision 2030 asserts the importance of developing the Saudi SMEs in order to diversify the economy and improve employment (Kingdom of Saudi Arabia, 2017). My study is conducted at the dawn of this historical moment and aims to provide a scientific approach to Saudi financial institutions to enhance their understanding and improve their ability to model the credit risks of Saudi SMEs, which, hopefully, will contribute to the grand 2030 vision of the country.

The credit default prediction model developed in my study is among the first to model specifically the credit risks of Saudi SMEs. In general, the model is highly consistent and accurate, which, using a 25% cut-off point, accurately predicts 88% of the defaults even using out-of-sample data. In addition, my approach also gives pricing guidelines to determine the credit spread based on firms' corresponding risk of default. Overall, examining a sample of 14,727 firm-year observations for Saudi SMEs between 2001-2011, I conduct the first systematic study to model and price the credit risks for Saudi SMEs. I hope this study can be widely applied in Saudi and beyond, and used as a foundation for future development.

8. IMPACT ASSESSMENT: Modelling Credit Risk for SMES in Saudi Arabia

8.1 Introduction

The small business sector is gaining momentum in today's economy because of its role as an economic stabilizer during difficult periods (Varum and Rocha, 2013). Consequently, the topic of small business credit is highly significant. As a result of fierce competition in retail and large, corporate lending segments, banks in Saudi are trying to take advantage of the untapped high potential for the growth of the small and medium enterprises (SMEs) lending sector. This trend reflects the Saudi Government 2030 Vision, which directs local banks to increase credit for this important segment of the economy (Jadwa, 2017). However, banks are still unclear about how to approach small business credit, leaving many questions unanswered, such as how lenders should assess small business credit and what credit risk models they should apply in order to grow the SMEs portfolios to make them profitable. Most of the current credit-risk models apply only to large corporations, with a few cases designed for SMEs application (Altman and Sabato, 2007). My research fills this gap with a focus on Saudi SMEs.

The impact assessment of this project provides evidence from my engagement with experts in the field of small business lending and investment. This chapter presents the results of what was planned in the impact stage of my DBA research journey[12]. The results stem from engagement with practitioners from the Saudi banking sector involved in SMEs financing as well as government representatives participating in Saudi 2030 Vision. In the chapter, I discuss the dissemination of the findings at international

[12] One of the DBA deliverables is the Impact Plan, which was completed in June 2016.

conferences such as Euromoney, Institute of International Finance (IIF) Middle East CROs' conference and regional media. In addition, the chapter covers the application of the thesis' credit risk model in a project between Saudi Arabian Monetary Agency (SAMA) and Saudi SMEs Authority in order to promote SMEs access to credit in line with Saudi 2030 Vision. The impact assessment takes into consideration ethical and practical considerations as well as the limitations of the research.

The remainder of the chapter is structured as follows: section 8.2 assesses the impact and contributions of the research; section 8.3 details the impact of the engagers throughout the research process; section 8.4 reviews the progress of the research dissemination; section 8.5 covers the practical application of the research; section 8.6 evaluates the impact of the study; and finally, a conclusion closes the chapter.

8.2 Contributions

Although this research has a focus on Saudi Arabia, given that there is a clear issue with respect to financing small businesses there, it can also be applied to many other countries because the issue of small business lending is a global challenge. One of the Saudi 2030 Vision's primary objectives is to promote SMEs access to credit (Jadwa, 2017).

Parallel to the Research Council United Kingdom's (2017) review on pathways to impact, this study makes several contributions to both academic and business arenas. First, the study develops a model in line with Altman and Sabato's (2007) model to predict credit default for Saudi SMEs, which are different from the ones employing the U.S. and U.K. data. This is, to my knowledge, the first systematic research undertaking to develop a default prediction model (or bankruptcy model) for Saudi SMEs. Second, in terms of practical contributions, the model can be useful for measuring the credit risk of SMEs in GCC countries and, perhaps, in other emerging markets as well. Financial institutions with SMEs clients' data-sets can further enhance and create internal credit-risk models by following the steps outlined in this research. With more accurate credit-risk models, the risk management of the financial system as a whole would be improved significantly. The model, with its enhanced dataset, can be further developed by the Saudi Arabian Monetary Agency (SAMA) and Small and Medium Size Enterprises Agency (SMEA) using Quaiem services (Ministry of Commerce and Investment, 2016)[13].

One of the goals of this study is to offer practical contributions to financial institutions with regards to unexplored areas of business. These practical tools could support their ability to approve credit to eligible small business entities, which would ensure good returns coupled with minimal losses. Moreover, having a robust credit risk model for SMEs would also help banks to meet Basel Accord[14] requirements for capital adequacy (Altman, 2001).

In line with the Economic and Social Research Council (2017), the impact on the DBA will be defined broadly; the beneficiaries of this research range from individuals and/or corporate entrepreneurs, financiers, policy bodies and credit agencies that operate within the Small and Medium Size Enterprises (SMEs) context. Practitioners were selected from each of these main beneficiary groups with the aim of assessing this study based on their relevant experience and expert knowledge in the field. This chapter results from efforts to transform the knowledge from the broader academic study into practice. The importance of this contribution lies in offering improvements to practitioners that

[13] Quaem is one of the Saudi Ministry of Commerce and Investment projects that collects and statistically analyzes the audit annual financial statements of all companies licensed to work in Saudi Arabia. I am involved in a project that coordinates between SAMA and SMEA in order to promote funding access to Saudi SMEs as part of the Saudi 2030 Vision.

[14] Basel Accords I, II and III are set by the Basel Committee on Bank Supervision (BCBS), which provides recommendations on banking regulations regarding liquidity, capital, credit, market risk and operational risk (see bis.org).

ultimately lead to an increased understanding and effectiveness of small business financing.

8.3. Engagement

Since this project develops a credit risk model for Saudi SMEs, it has been important to engage with lenders and credit officers working in the SMEs sector. It has also been important to interview people directly who deal with small businesses in order to learn their views on the issue of handling the credit side of this sector. This impact assessment identifies beneficiaries and users of this research and a group of practitioners in the finance field to evaluate the relevance of the research to practice. They have advised and aided me in utilizing and disseminating the work to promote small business financing.

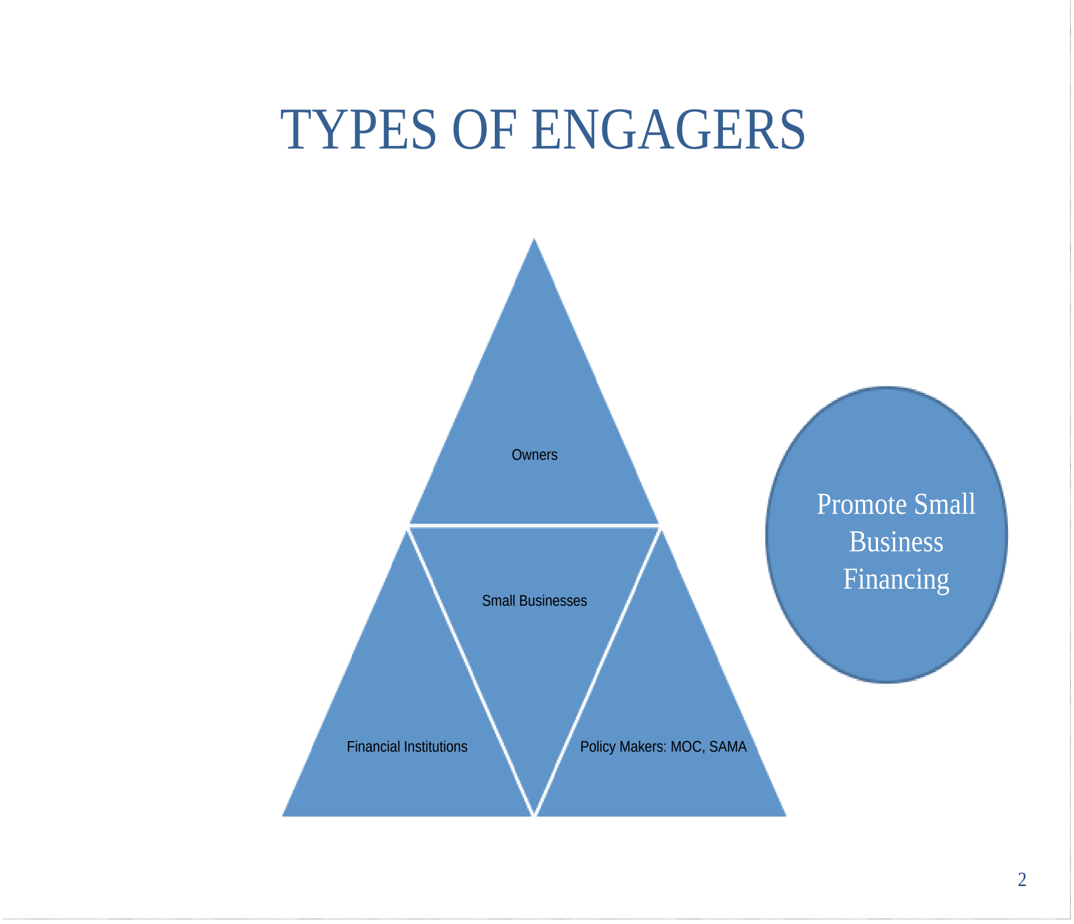
The chapter identifies how the subgroup of beneficiaries, who act as practitioner advisors, can contribute to and utilize this research to increase its value in practice. Verification of the impact and value of the research for practitioners has been obtained through testimonials from beneficiaries.

8.3.1 Types of engagers

Among the beneficiaries and users of this research in the finance world, there are financial institutions—including banks, finance companies and regulatory bodies, such as the Ministry of Commerce and the Saudi Arabian Monetary Agency (SAMA)—and indirect beneficiaries, including government agencies charged with creating civil social benefits, potential non-profit organizations and the recipients of social outputs in society in general. Since the focus of this work is on handling the credit risk of small businesses, the impact assessment mainly addresses some of the direct beneficiaries, which are the financial institutions that will serve the credit needs of small businesses. For the purposes of this chapter, beneficiaries considered for advisory roles in this impact study derive from a pool of bankers and policy makers. Figure 8 depicts the different types of engagers within this chapter.

Figure 8: Types of engagers

In considering these groups of beneficiaries, all would likely benefit from a more detailed and evidence-based understanding of how to handle the credit risks of small businesses. With this model in hand, small business owners would be more familiar with



the types of requirements by lenders when they seek finance for their businesses. Banks and finance companies would discover an appropriate approach to handle and manage the credit aspects of small businesses in order to grow a balanced credit portfolio with a stable return and an acceptable default risk. Government agencies, including the Central Bank, which manages the banks and finance companies, would see the small SMEs sector grow and contribute to the economy and society because the growth of the small business credit sector has led to the improved welfare of society and growth in the GDP.

8.3.2. Results & contributions of the engagers in this research

Practitioners have been involved throughout the study in providing the data for the empirical work, offering practical suggestions, reviewing the findings of the research and disseminating the findings. In particular, I have identified and engaged with the following people involved in the SME credit sector:

1. **Turkey Alhamdan**, Senior Manager at Samba Financial Group. Alhamdan has dealt with many small business sectors and is familiar with relevant financing requirements as well as the challenges facing such a sector. He has also dealt with small businesses through the quasi-government program Kafalah, which provides guarantees to participating banks that deal with small businesses with exposures capped at Saudi Riyals 2 million and/or 80% in the form of the guarantee of extended exposure. According to Alhamdan, SMEs' contribution to the economy is still underestimated because they are not given the types of facilities necessary for their noticeable growth and contribution. SMEs lack proper funding because of financiers' rigid requirements.

   Saudi banks can be classified into two categories: rigid banks and easy banks. Rigid banks are the banks that do not differentiate between small businesses and large businesses. This is because they lack an understanding of the nature of small businesses. They ask for audited financial statements and business information, which are not easy for the average small business sponsors to provide. Easy banks, or financers, are those that ask for less detailed information from small businesses.

According to Alhamdan, it has been noticed that even easy banks have now started to ask for more information as a result of growth in credit portfolios and that they do not want to expand their risk with this sector. Alhamdan sees the small business credit portfolio grow but not to the levels that are satisfactory to the stakeholders. The growth should, ideally, be more rapid in order to create the anticipated added value.

When we talked about the application of my credit risk model, he stated that he thinks it is an effective model to be used in Saudi Arabia. He is, however, concerned with the macroeconomic situation in the country due to the drop in oil prices and its impact on the liquidity in the market. Most of the liquidity goes toward financing the government deficits with an emphasis first on government agencies and then on quasi-government projects. This could delay the growth in financing the small business sector. Alhamdan thinks that most financiers lack a proper credit scoring model. He sees a great opportunity for a wide application of my credit risk model for Saudi banks and financing companies (Alhamdan, 2016).

2. **Guhan Ramkumar**, Senior Manager at Samba Financial Group, has dealt with small- and medium-sized companies in both the credit and sales sectors. He has helped me in selecting the quantitative and qualitative variables used in the credit risk model. He is encouraged to see that I have developed a solid credit risk model, which, he believes, is ideal for pricing the credit risk of Saudi SMEs.

He adds that the credit-risk model could represent an attractive opportunity for a financial institution because it would yield better returns by offering multiple business-credit-lines at small scales that carry higher returns. Moreover, the model, he notes, can support credit decisions and be tailored to the tenor of business loan needs. The credit model considers several dimensions including the size of the firm, the profitability, indebtedness and qualitative variables relating to customer and suppliers, geographic areas and business sectors, etc.

Furthermore, he offers, the credit risk model provides a solid ground for the target market given its high (out-of-sample) accuracy in predicting defaulted SMEs. He did, however suggest that a target market sheet be developed to carry the actual figures of the prospective obligor vis-à-vis the defined criteria and approval level, where permitted (Ramkumar, 2016).

3. **Osama Al-Mubarak**, Head of Kafalah Program under the Ministry of Commerce. One of the objectives of this quasi-government program is to promote the small business credit environment by offering support to small businesses that require guarantees while dealing with lenders. Al-Mubarak has been with the Kafalah program since its establishment and was one of its founders.

   Al-Mubarak has been engaged with the research. He believes that the developed model has the potential to overcome the dearth of knowledge in handling small business credit risk. According to him, the Kafalah program has been exploring the opportunity to collaborate with the Saudi Credit Bureau (SIMAH), which works as the official, local credit bureau. SIMAH keeps records of all types of borrowers in Saudi Arabia and is working to devise a system that gives a rating to borrowers including individuals, small business, medium businesses and large businesses. My credit risk model can be tested and applied in this project.

Specifically, according to Al-Mubarak, the credit risk model can be used as a guide in making credit judgments. His engagement has been of great help in developing the scoring model.

Specifically, Al-Mubarak discussed a program initiative designed to create a portal for small business fund-seekers to provide their data to potential lenders in a professional manner, which could be processed using my rating model. This model could be available to banks and credit providers, which would reduce the time needed to gather the necessary information for financers, ensuring commitments by small business owners. This could be crucial in shortening a significant stage in the credit assessment of small businesses. Besides SIMAH, the Kafalah program is also working with the International Finance Corporation (IFC) to promote small business lending in Saudi Arabia, where my model can be potentially introduced and applied (Almubarak, 2016).

8.3.3. Other engagements

During several stages of the research, including the data collection stage, I referred to several experts in the arena of small business credit. I dealt with subject matter experts in data collection who helped to identify the key variables used in the credit risk model. The practitioners have offered valuable advice and suggestions based on their rich experiences. The details of the engagement with practitioners (i.e., interviews and meetings) in discussing small business credit have helped to shape the research concept.

The following testimonials derive from subject matter experts in the Saudi and GCC economies including private sector leaders and members of government institutions.

According to Mohammed Elkuwaiz (2017), Vice Chairman, Capital Market Authority, Riyadh K.S.A.:

> *"I am grateful for Naif's efforts. I am also hopeful that his work will fill a valuable knowledge gap, thereby contributing to more sound and evidence-based decisions with respect to credit provided to SME's and ultimately to helping allocate capital more efficiently to emerging business."*

In the words of Tirad Mahmoud (2017), CEO of Abu Dhabi Islamic Bank, Abu Dhabi, UAE:

> *"This is an important project. It is particularly relevant for the K.S.A. and the GCC in general. In the GCC, the credit loss norms of this sector are higher than what has been experienced in other advanced economies such as Italy, Canada, U.K., USA etc. I suggest that you seek help from SAMA as they may have statistical information on defaults and losses in the event of default that can be helpful to you. If SAMA can't assist, the banks with the organized data bases are NCB, samba, Sabb. There are reasons that caused the higher probability of default and losses in the event of default in our region. Most likely the reasons relate to the ineffective legal environment regarding collateral security etc. Supporting the SME sector is essential for economic growth and job creation in the GCC. Banks and central banks will benefit from such a study that should*

potentially help in recalibrating the credit policies and pricing so that the lending practices become sustainable."

According to Sajjad Razvi (2017), Ex-CEO and Board Member of Samba Financial Group, Riyadh, Saudi Arabia:

Naif, I feel you have chosen a most relevant subject for your Doctorate Paper. As we know the biggest employer in Saudi Arabia is the SME sector and it has a Spinal Cord Role in the Economy and contributes the most for Socio-Economic Stability. A model based approach to SME sector can promote transparency and thus further growth in the SME sector. It will also induct gradual upgrading of Governance across SME. With higher transparency and governance, the banks will be willing to increase portfolio allocation to SME.

As we know, today banks in Saudi are still more driven towards bigger businesses and if they are provided a tool and risk predictor for the SME Portfolio, they will be able to price it where risk adjusted returns are such that it would warrant higher allocation of risk appetite and credit portfolio. Moreover today in absence of such a model, banks mostly lend short term to SME Segment, which limits Investment in SME and forces it to underperform vs its potential in the economy.

With higher allocation of portfolio, higher investment and thus higher employment, the impact on Economic Growth and Socio-Economic Stability in the medium term will be tangible and sustained.

The introduction of new management processes and technology will also commence. And With that access to Capital Markets will commence, thus diversifying sources of funding and tenors from Debt Markets. Of course the *integrity and credibility of the data behind the SME Credit Risk Model will be key and its testing should be independently validated. The Regulators and Rating Agencies can help along with the financial sector for the development and software of the model. As head of Samba Financial Group, we had commenced this project with the regulators and work was still in process. Wishing you all the best on this paper and I am happy to amplify further, if needed."*

Khalid Al Gwaiz (2016), CEO of ACWA Power Holding & Board member of Rajhi Bank, Riyadh, K.S.A., said:

I am pleased to learn that you are finalizing your doctorate research thesis on Modeling Credit Risk for SMEs in Saudi Arabia. Having worked with you from 2003 to 2007, as well as being a close associate ever since, I am sure that you will achieve brilliant results.

Small and medium-sized enterprises (SMEs) are among the most important agents of economic growth; they create jobs, support innovation and boost exports. But as you know, SMEs in Saudi Arabia are not yet major contributors to the GDP. This is set to change with the attention the sector has been receiving over the last few years. The country's vision 2030, which aims to transform and diversify the economy, has established the SME Authority and declared plans to continue encouraging local entrepreneurs with business-friendly regulations, easier access to funding, international partnerships and a greater share of national procurement and government bids.

The Central Bank has also placed strong emphasis on devising special lending schemes to SMEs and established, in partnership with the banking *industry, special programs to enhance lenders' tolerance to SMEs risks. As a result, most banks (including the one which I am a member of its Board of Directors) have established dedicated and well-resourced SME divisions to avail the right focus and attention to this important segment.*

Knowing your capabilities and professional aspirations, coupled with your pursuit of advance studies of the subject, I expect you to stand out as a key figure among the players in this exciting segment.

I wish you the best of luck and look forward to hearing the good news upon receiving the final accreditation.

Take care.

According to Dr. Amro Adel Hassan (2017), Director of SMEs at Watan First Institute, K.S.A.:

The reviewer recognizes the importance of ensuring that the Credit Scoring model under review produces reliable results that assist in assessing repayment risk and help to meet the credit needs of creditworthy borrowers.

The undersigned reviewed the items attributes that are included as factors in the reviewed credit scoring system and have found them relevant and representable of the different risk factors in the K.S.A. SME market.

My review also found that the model's risk measurement is based on sound historical data, measures the risk of default and produces consistent results across time for a wide range of borrowers. Finally, examiners assessed the Model's scores to certain third-party vendor models for appropriateness and have found the results to confirm the reliability of the model under review

I also examined whether loan performance differed across several groups of borrowers. For every performance measure evaluated and for every borrower group considered, the model found that credit scores consistently rank-order the credit risk of scored companies.

The Model was further examined by running it over several SME borrowers and was found to produce results in line with the local scorings by the borrowers' bankers and conformant to their account performances.

This concludes my testimony regarding the SME credit scoring model by Mr. Naif Abdulmohsen Al Baz.

In line with the reviewers' thoughts, the risk management domain assesses the SME sector and covers the varied lending techniques followed by lenders. Lending involves appetites in terms of opportunities, obstacles and environment. This study aims to balance academic and practical approaches. There are many difficulties surrounding small businesses that constrain their growth. As such, this project attempts to address the problem and compare different solutions applied in international research domains. As discussed in the research, there is a clear gap in the literature with respect to implementing and rolling out models to deal with the credit risk of small businesses. This thesis attempts to bridge the gap for Saudi SMEs.

8.4 Dissemination

I have been disseminating the findings of this research by presenting it at finance conferences, such as the Euromoney Saudi Arabia Conference, which took place on 2-3 May 2017 in Riyadh. The conference welcomed 1,700 participants and received global media coverage. The conference raised and addressed financial challenges and opportunities in the Kingdom. The conference included special sessions on the efforts of the newly established Saudi General Authority for Small and Medium Enterprise (Ministry of Commerce and Investment, 2016; Euromoney Conferences, 2017). In the side sessions, I shared my research with respect to the development of the SMEs credit risk model. I benefited from the conference presentations and received follow-up meetings from several banks and venture capital firms that are trying to enter into the SMEs lending space.

I also participated in the Institute of International Finance (IIF) Middle East Chief Risk Officer Forum during April 2017 in Bahrain. The forum brings together risk officers from the Middle East to exchange ideas and valuable insights on key, current topics in risk and their implications for the region. I had the opportunity to share my experience creating a credit risk model. As with other conferences, I received valuable comments from several parties and requests to elaborate on my model.

I have also disseminated my findings through social networking, such as a WhatsApp group that includes about 100 academics, practitioners and writers for local newspapers, such as Al-Eqtisadia, a leading finance business newspapers.

In addition, I have broadcasted my findings through TV interviews with Arabic stations, such as Al-Arabia and CNBC–Arabic TV, that focus on Saudi banks and businesses. Moreover, I shared my experience at my former company, Deutsche Gulf Finance, when I was the Chief Executive Officer there.

Currently, I am involved with Quaem, which is one of the Saudi Ministry of Commerce and Investment projects that collects and analyses the audit annual financial statements of all companies licensed to work in Saudi Arabia. I am also involved in a project that is coordinated between Saudi Monetary Authority (SAMA) and Saudi Small and Medium Enterprises Authority (SMEA) that promotes funding access to Saudi SMEs as part of Saudi 2030 Vision. Through these various outlets, disseminating the results of the project has included describing the research process and the importance of having such a model to better handle the credit risk of Saudi SMEs.

This impact assessment also addresses the ethical and practical considerations as well as the limitations of the research. This project involves the collection of data from a single financial institution. The sensitivity of the data and the confidentiality of the clients' information has been guarded in the dissemination process. When I presented the results of the research to the target financial institution, I did so without disclosing the names of the portfolio clients.

The fact that the dataset is obtained from a single financial institution limits the research domain, however this may be mitigated as some clients deal with multiple financial institutions.

8.5 Application

During my tenure as an executive banker for more than seventeen years, I witnessed a decline in SMEs cases by the bank's credit committee. This observation led to the realization that these small business entities require a simpler and stronger format of borrowing in order to support their ambitions. There is a great potential for financial institutions to generate higher returns on assets by offering credit facilities that are tailored to these small business entities. This realization fueled my passion for this research. My hope is that this study will enlighten financial institutions in Saudi Arabia with regards to unexplored areas of due diligence, which will support their process of approving credit to eligible small business entities, thus ensuring higher returns coupled with minimal losses. That is because experts can apply this credit risk model to expand their credit exposure portfolios in the small business sector.

8.6 Evaluation of Impact

This project aims to have a positive and significant impact in the small business credit arena in Saudi Arabia. The study develops a scientific model to assess the credit risk of Saudi SMEs looking to grow in their businesses. Such tools can be used to grow the lending portfolio for this important sector of the economy. The model can also play a vital role in the long-term development of these businesses. Recently, after completing a four-year position as Chief Executive Officer at Deutsche Gulf Finance, I joined Gulf International Bank in January 2017 as the Chief Risk Officer. I have been overseeing the bank's policies with respect to the midcap portfolio, benefiting directly from my SMEs doctoral academic study in addition to my previous practical experience. I have also taken a recent assignment as a board member for Bayan Credit Bureau licensee of the Saudi Monetary Authority (SAMA), the Central Bank. One of the products that this agency will be covering is the rating of SMEs, and I will contribute to the development of this product.

8.7 Concluding Remarks

It is important to assess the impact of the project in the field of small business credit in Saudi Arabia. This has been achieved by engaging with the practitioners throughout the research process. The impact assessment has involved several steps including the engagement with the experts and potential beneficiaries who have contributed to achieving the objective of developing the scientific model to assess small businesses credit in Saudi. The impact assessment includes disseminating the concept and results of the project through international conferences such as the Euromoney, Saudi Arabia and IIF's Chief Risk Officer Conference. It also covers the conversion of the ideas and findings into products such as tools, diagnostics, guides, rules, or consultancy. Finally, the impact assessment considers the broad contribution of the work to individuals, organizations, society and the economy.

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