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Survival of the fittest Small and Medium Enterprises: Accessing commercial bank funding in South Africa

A Dissertation

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By

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ABSTRACT

Small and Medium Enterprises (SMEs) are touted as engines of sustainable economic growth. They span a wide spectrum of economic domains and are inclined to foster innovative entrepreneurship and gratify a variety of socio-economic objectives such as poverty alleviation, income generation, employment creation and reduction in societal inequalities. The SME sector in South Africa is challenged by slow growth in young businesses and dying at infancy due to lack of financial support. Inadequate funding results from a myriad of factors which include comprehensive enforcement of regulatory requirements, information asymmetry, moral hazards, lack of sound information on credit performance and technological divide. This study investigated this funding conundrum by assessing the success rate of SME applications for commercial funding. A quantitative cohort analysis was used on overdraft facilities obtained from one of the leading financial institutions in South Africa to determine the drivers of default.

A time series view of macroeconomic factors and macroprudential indicators in conjunction with the demand and supply trends was analysed using vector autoregression techniques to determine the impact of the economic environment and financial market condition on access to funding. Unit root tests and cointegration analyses were applied to examine stationarity, short-run and long-run relationships. The SME scorecard was developed using logistic regression on cohorts of applications over a seven-year observation period to determine the drivers of default as part of credit risk management. SME application scorecards were developed including and excluding bureau information. The ensuing models' ability to differentiate risk were assessed using Receiver Operating Characteristic (ROC) curves.

The results show that, the demand and supply of SME credit is influenced by trends in the domestic, economic and financial environment. The robustness, stability and relevance of an application scorecard is enhanced by reject inference and the inclusion of bureau information. Small businesses operating in the service sector and having a long-standing rapport with the bank can easily access commercial bank funding. SMEs in the construction industry with a high number of credit enquiries are unlikely to survive the stringent conditions of the bank lending criteria. It is the prerogative of the principal business owner to honour their financial obligations across the credit industry if commercial bank funding is desired. Their credit quality forms the fulcrum of the lender's SME application scorecard.

DEDICATION

I dedicate my thesis to my pillars of strength: God Almighty, my daughter Kudzai Munemo and my parents, Mr. Josephat Dzikiti and Mrs. Cecilia Dzikiti, for their much-needed tender loving care, moral and spiritual support.

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CHAPTER 1: INTRODUCTION

1.1 Background

Small and Medium Enterprises (SMEs) are broadly defined as distinct business entities that maintain turnover, number of employees and gross asset value below or equal to pre-determined limits (Keskin et al., 2010). Thresholds are set by countries or governments and the limits vary across the globe depending on jurisdiction and economic landscapes. Segmentations can be applied to small businesses based on actual size, economic sector and other country specific variables and this accords SMEs different nomenclature across the globe. SMB is an acronym for Small to Mid-size Business in the Unites States, MSME stands for Micro, Small, and Medium-sized Enterprises in Kenya, MSMED is an Indian acronym for Micro, Small, and Medium Enterprise Development and SMME represent Small, Medium and Micro-sized Enterprises in South Africa (Chimucheka & Rungani, 2013).

Despite the differences in naming conventions around the globe, SMEs share the commonality of segmenting small businesses by size or structure, with a clear-cut definition used to distinguish them from large corporates (Keskin et al., 2010). Furthermore, SMEs can be categorised according to size by economic sectors or domains of specialisation such as manufacturing, distribution, property, trading, retailing, import-export, construction, catering, mining, agriculture, amongst others. According to the South African National Small Business Act (1996), SME segmentation is particularly important for the purposes of resource allocation by governments, financial institutions and other SME supporting entities.

Keskin et al. (2010) indicated that SMEs span a wide spectrum of economic sectors and are inclined to foster innovative entrepreneurship and gratify a variety of socio-economic objectives such as poverty alleviation, generation of income, employment creation, economic growth and reduction in societal inequalities. Their study showed that, in high income countries, SMEs contribute roughly 55% to GDP and approximately 65% to employment. In low income economies, SMEs account for about 60% of GDP and 70% of employment. This is supported by the World Bank Group (2018) statistics and other various pieces of research showing similar levels of contribution to the economy. Generally, SMEs are touted worldwide as engines of economic growth and this warrants SMEs full attention in this study.

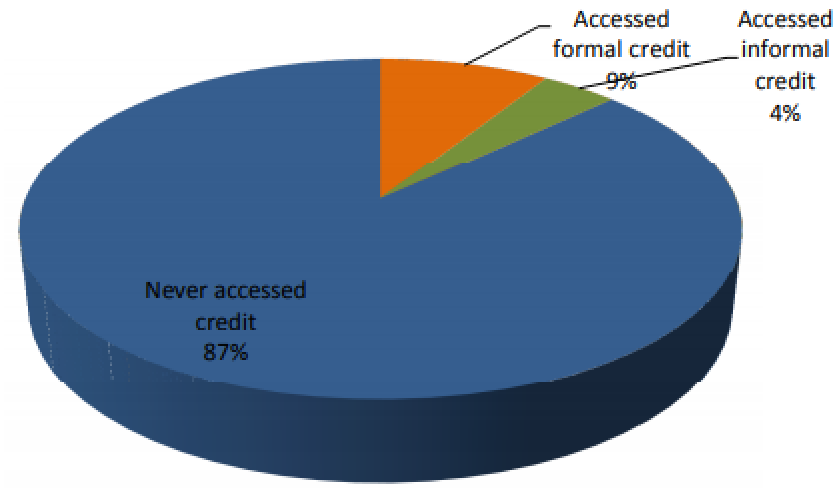
Having to start small, SMEs can be viewed as the nursery for future large corporates. Large firms such as the Ford Motor Company, founded by an American born Henry Ford (Edmunds, 1952); the Canadian Advanced Light Imaging (A.L.I.) Technologies Inc., a medical industry firm started by Peter Keefe (Kovac, 2009); the South African fast food chain, Spur Steak Ranches, a brainchild of Allen Ambor (Spur Group, 2012); the Chinese trading firm, Alibaba, formed by Jack Ma (Schuman, 2014) and the Capitec Bank in SA, founded by a consortium of micro-lenders (James, 2014) are examples of companies that started as SMEs before they developed into large corporates. However, high growth of SMEs into large corporates are exceptional and rare (McKelvie & Wiklund, 2010). In as much as their coverage is wide and their worth is recognised and commended, there exists a multitude of challenges inhibiting SME growth and performance across the globe (Anderson & Ullah, 2014). Growth is suppressed in small businesses by design or by default.

A study conducted by Anderson and Ullah (2014) revealed that growth inhibition by design is attributable to aspects of negative attitude and lack of motivation. Some owners choose to remain small in order to avoid growing pains and potential hazards associated with growth stages over the business life cycle. Growth inhibition by default is driven by the general dynamics in the operating environment and economic landscape. Limited resources in the areas of finance, shortage of skilled human capital, poor planning and lack of expertise, education and training are some of the major sources of perpetual smallness (Fatoki & Garwe, 2010). Businesses remain operational but are maintained at infancy stages of growth. The worst-case scenario entails closure of businesses which cannot withstand intense growing pressure owing to some of the circumstances described above and other growth inhibitors. SME growth, development and success dynamics are therefore diverse and complex. Growth is inhibited due to of access to commercial bank funding (Chimucheka & Rungani, 2013) among other factors.

1.2 Problem Definition

Most of SME financing options are limited to inception stages of a business cycle, which contribute to seed and initial growth funding. From inception, small businesses are largely funded through personal savings, family, friends, donations, business angels, retained earnings, etc. (Chimucheka & Rungani, 2013). As businesses develop and expand, a wider spectrum of funding is sought to finance operations and rapid growth, one of which is commercial bank loans. However, SME accessibility to commercial funding is limited (Mutezo, 2015). Lack of adequate funding is the main operating and growth constraint of SMEs (Berger & Udell, 1998). As SMEs form an integral aspect of most economies globally, it is crucial to investigate this constraint and suggest ways to mitigate the challenge. Most researchers base their analysis on primary, survey data, though in different timelines but their results point to similar conclusions. Figure 1 can be used as a statistical view encapsulating the state of access to finance when survey data is considered. Of the registered SMEs in South Africa, the success rate of accessing formal credit has been observed to be 9% (Makina et al., 2015)

Figure 1: Access to Credit by Registered SMEs



Source: Makina et al., 2015

Given that vast research on SME funding in South Africa is based on cross-sectional data, it is difficult to make a causality claim when establishing the link between SME specific attributes and access to finance (Makina et al., 2015). This study therefore seeks to utilise longitudinal secondary data to perform regression analyses to shed more light on factors affecting the success rate of SMEs in accessing commercial funding. The behaviour of borrowers during their credit term is investigated. The result is mainly used by the credit lenders in determining applicants who are eligible for funding based on the presumption that past trends predict the future. Of importance is the inclusion credit bureau information into the analysis. This encapsulates the market wide behaviour of applicants. If the applicants were granted loans from other finance houses, it is difficult to obtain their default tendencies directly from other lending peers due to bureaucracy and red tape issues. The applicants' credit bureau information therefore becomes pivotal and a good proxy in picking up the holistic credit behaviour of borrowers as this information is generated based on feedback from the entire credit market.

Whereas primary data may restrict researchers to a specific jurisdiction or industry, this report encapsulates a countrywide view of applications over time from different sectors and geographical location of the South African economy. With large datasets to be extracted over time, this analysis is set to provide more stable and robust view of the SME credit patterns.

Further, given that South Africa is one of the most industrialised economy on the African continent with leading financial markets (Makina et al., 2015), the analysis will help understand if this benefit filters through SME funding and growth. The main problem to be investigated is the determinants of the success rate of SMEs' access to commercial funding in South Africa. This will be done using a comprehensive advanced statistical model, making use of a wealth of longitudinal historic information. To the best of our knowledge, inadequate funding of SMEs by financial institutions in South Africa is as a result of a myriad of factors which include: comprehensive enforcement of regulatory requirements, lack of collateral, information asymmetry, moral hazards, lack of sound track records on credit performance, technological divide between lenders and borrowers and lack of financial records. Investigating the financing conundrum of South African SMEs through tracking cohorts of SME loan applications forms the fulcrum of this study.

1.3 Research Questions and Objectives

This research seeks to provide answers to the following questions:

- What is the correlation between the demand of SME credit against the South African economy and credit market industry?
- What is the correlation between the supply of SME credit against the South African economy and credit market industry?
- What model can be used in establishing drivers of default based on the availability of external information such as bureau information?

The main aim of this study is to investigate the success rate of SME application for commercial funding using data obtained from one of the leading financial institutions in South Africa. Following is a list of research objectives:

1. *To assess the relationship between the demand of credit against the economic and credit market industry growth.*

2. *To assess the relationship between the supply of credit against the economic and credit market industry growth.*
3. *To identify drivers of default and determine how the model is affected by introducing external information such as bureau data.*

This study seeks to test the following hypotheses.

Hypothesis 1: The volume of SME loan applications (demand) is a function of industry wide credit market activity and economic growth as reflected in key macroprudential indicators and macroeconomic factors.

Hypothesis 2: The acceptance rate (supply) of loan applications is a function of industry wide credit market activity and economic growth as reflected in key macroprudential indicators and macroeconomic factors.

Hypothesis 3: The SME application scorecard is a better fit than a null model. The robustness of the scorecard is improved by the inclusion of internal and external risk drivers in the model.

1.4 Scope of the Study

This research explores secondary quantitative data obtained from a consumer credit context. The data herein are analogous to lifetime data as they show a cohort of credit consumers with different loan repayment behaviours over a given observation period. The commercial bank product offering chosen is the Overdraft (OD) facility. This is a type of loan that is linked to a transactional account, usually a Cheque account. It allows the account holder to withdraw money in excess of the credit balance up to an approved credit limit.

Customers (SMEs in this case) can utilise the full limit granted or a portion thereof and interest is charged only on the utilized portion of the OD. This loan facility accords customers the flexibility to transact, drawdown, repay and utilize again within the bounds of the credit limit, making the facility both transactional and revolving. For this study, the dataset consists of loans applications presented to the bank between July 2012 to July 2019. Application and behavioural variables are provided for each loan. Of interest in this study are application variables representing standard information provided by through the door customers because the model will be applied to this population.

1.5 Justification of the Study

This study seeks to identify factors leading to the acceptance or rejection of SME application for commercial funding. Importantly, growing a quality SME portfolio is vital from both the lenders' (supply side) and SMEs' (demand side) perspective. Furthermore, in the developed world, corporate and retail segments are gradually offering limited opportunities for credit expansion (Caire, 2009). Evidently, the SME sector offers high yields and an attractive market segment. This trend is likely to filter into the developing market as well given that this part of the world trails behind the developed economies in various aspects including SME growth. Resultantly, the lenders need to build good quality portfolios which is the main offering in this study. As discussed in Section 1.1, the SME sector forms the backbone anchoring the future growth of many economies across the globe. To enhance meaningful contribution to employment rate and economic growth and development, SME progression need to be substantiated by increased credit. What banks perceive as good risk clients eligible for approval of commercial bank funding is another offering in this study. Thus, the justification of this study emanates from the potential benefits envisaged for the lenders and the borrowers within the SME credit market as well as the benefits accrued to the South African economy at large.

1.6 Organisation of the Study

The study is organised as follows:

- Chapter 1 introduces the research work while outlining the background, context of the work, the problem statement, research questions, aims and objectives. The research justifications, motivation and contributions conclude the chapter.
- Chapter 2 presents the literature and theoretical background to the SME credit market. Literature review is linked to the research questions and objectives given in Chapter 1, highlighting issues in development finance with regards to SME credit market. Credit risk management concepts, the possibilities and pitfalls associated with various approaches to model risk form part of literature review as well.

- Chapter 3 describes the methodologies followed. This chapter broadly describes the research design and research methods. It provides details around data collection instruments and the specific features on the relevance of the methodologies employed.
- Chapter 4 details the key results, including statistical analysis and whether the results are significant. As a matter of good practice, some of the primary evidence in this section will be presented in the Appendix section as appropriate.
- Chapter 5 concludes the study while proposing recommendations, mitigation solutions to the SME financing problem. The chapter evaluates that the objectives of the study are met and propose recommendations for to the relevant stakeholders including future research ideas.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This section presents theoretical and empirical review of the SME financial market: challenges presented through credit lending to SMEs, data requirements to facilitate lending, the economic and financial landscape driving demand and supply of SME credit as well as credit scoring and applicability of credit risk management concepts within the SME framework.

2.2 Definition of Terms and Concepts

This section discusses the terms and concepts which will be used throughout the study.

2.2.1 Credit Lending

Credit refers to borrowed money that SMEs can use to purchase goods and services required for their operations to run (Sumit et al., 2006). SMEs obtain credit from a credit grantor, the commercial banks in this case with an agreement to pay back the amount borrowed plus applicable finance charges, within an agreed time frame. Credit can be granted in various forms enlisted herewith: *Revolving credit*, where a maximum credit limit is granted and the borrowers can utilise up to that limit, *Charge cards,* where total balance need to be repaid or settled every month, *Service credit* in which the borrower receives services with charges settled monthly and *Instalment credit* where regular instalments of fixed amounts over a fixed time period are paid (Hendricks, 2011). Examples of instalment credit are vehicle finance and mortgages. As discussed in section 1.4, the scope of this study is based on a revolving credit type of lending known as overdraft facility which can be sought to meet SME liquidity needs. It is important to note that, with OD loans, SMEs pay interest only on the utilised portion of funds drawn against the total commitment.

2.2.2 Credit Risk

Credit risk refers to the potential hazard that the borrower may fail to meet contractual obligations, that is, failure to make the required payments (principal amount and interest thereof) resulting in them defaulting on the loan (Hendricks, 2011). The risk is that of the lender as this amounts to cashflow disruptions and arising steep debt collection costs, sometimes unforeseen. As part of credit risk management, the lender thrives to maintain credit risk exposure within acceptable parameters derived from its risk appetite and risk tolerance. This filters through the loan granting landscape. When lending to borrowers, credit grantors make use of the applicant's credit record to determine the financial risk as a way to minimise financial losses. The credit information, encapsulated in the bureau credit score is often the primary resource guiding the grantor's decision. A credit score is a number that reflects the applicant's creditworthiness. Good risk customers are normally assigned higher scores and favourable loan pricing conditions. It is therefore imperative for SMEs to maintain a good credit record in order to take advantage of the convenience credit can provide. Credit Rating Agencies (CRAs) provide lenders with the bureau score at an agreed fee. On the South African credit market, the retail sector bureau scores are often obtained from CRAs such as TransUnion and Experian. This study will make use of the SME principal owner's bureau information obtained from Experian, as a proxy for the SME performance on credit facilities.

2.2.3 Credit Rationing

Credit rationing is a market imperfection or market failure phenomenon. Lenders tend to apportion the supply of credit based on market conditions and their risk appetite (Mutezo, 2015). Credit rationing occurs due to information and control limitations in the financial markets. This event reflects failure of price mechanisms which in turn miscarries market equilibrium. SME credit industry suffer credit rationing when SMEs fail to provide sufficient collateral to hedge against potential credit losses by the lenders.

2.2.4 Information Asymmetry

Information asymmetry is a market failure problem encountered within a financial system due to inequalities in the distribution of information (Ocran, 2012). It is crucial to gather adequate and reliable financial information for any sound financial decisions. Information asymmetry results in opportunism, in instances where parties with better quality and quantity of information benefitting at the expense of the other parties with information of less quality and quantity. This phenomenon contributes to market inefficiency in development finance particularly with SME credit market.

2.2.5 Adverse Selection

If parties take advantage of information asymmetry ahead of a transaction, this potentially results in a scenario referred to as Adverse Selection (AS). In the SME credit market, lender is confronted with the challenges of failure to differentiate good and bad risk loan applicants because the borrower might have information that the lender may not have. Failure to establish this distinction may cause lenders to price loans with the same interest rate. This tends to penalise good risk borrowers and reward the bad risk, hence the term “adverse selection”. In economics theory, the consequence that AS brings is that, due to high interest rate, safe projects (low risk SMEs) will have a lower rate of return (Ocran, 2012). This leaves high risk projects in the market with banks charging even higher interest rate to reflect their high-risk loan portfolio. If the market is awash with bad projects, this is nicknamed the market for lemons in economic theory (Akerlof, 1970).

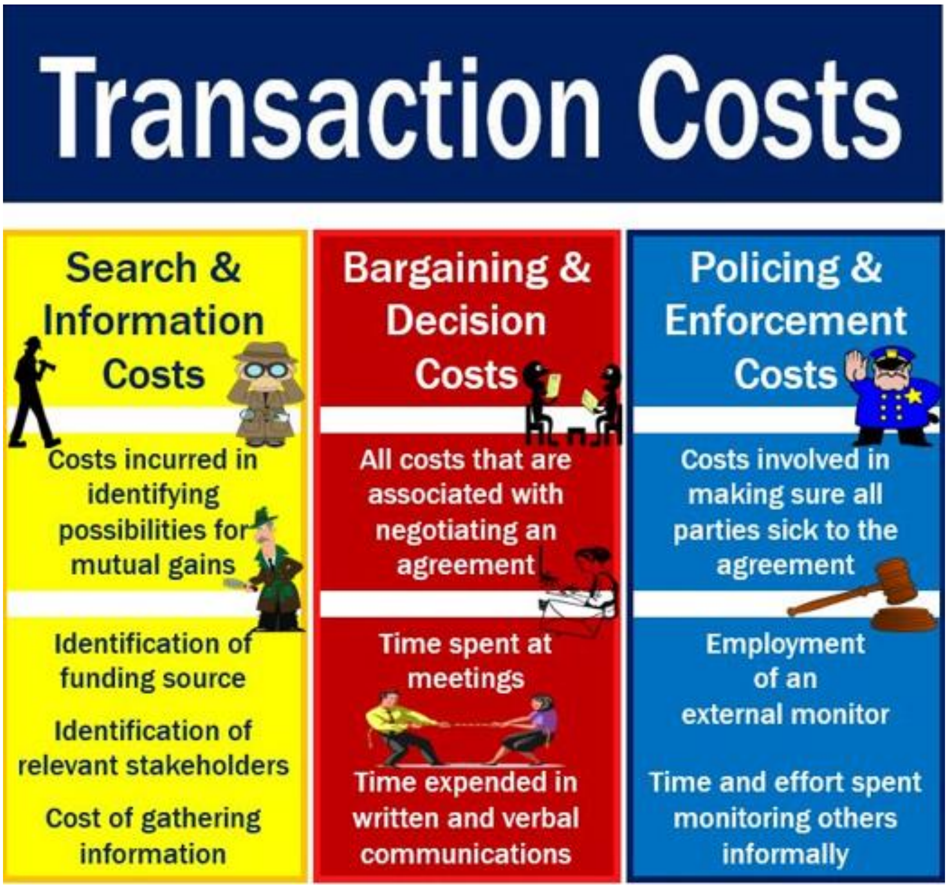
2.2.6 Moral Hazards

If parties take advantage of information asymmetry after a transaction, this becomes a market failure phenomenon called Moral Hazard (MH). The contract places incentives upon one party to take immoral behavioural steps which can be unobservable but are prejudicial to another party in the transaction who bears the fallout (Ocran, 2012). AS and MH prohibits the markets to allocate resources efficiently. In SME credit market, MH occurs when the borrower has already acquired the loan, violate the original commitment and engage in high risk investments. After the transaction lenders are not completely in control of what SMEs use the funds for. MH tends to high levels of bad debt and lenders take a toll. To ensure profitability and safety, some lenders implement credit rationing programs (Huang et al., 2014).

2.2.7 Transaction Costs

In economic theory, a surcharge incurred in making an economic or financial exchange or the cost to participate in a market is known as transaction cost (Ocran, 2012). As shown in Figure 2, transaction costs includes but not limited to the cost of research, negotiations, processing and storage of information; cost of execution and monitoring of the transaction (Ocran, 2012). For SMEs to participate effectively in the credit industry, the governments needs to play a role in creating an operating environment that reduces transaction costs thereby improving the viability of SME operations (Huang et al., 2014).

Figure 2: Transaction Costs



Source: (Ocran, 2012)

2.3 Theoretical Framework: Information Asymmetry and Lending

According to a study by Duan, Han, & Yang (2009), information asymmetry is the leading contributing factor of credit rationing. Uncertainties in the behaviour of SMEs makes lenders face AS and MH challenges. Furthermore, if SMEs fail to provide standardized financial statements, the lender remains limited in knowledge about the borrower (Badulescu, 2010). In Belgium, there are important disclosure and audit requirements in standardisation of the financial reports (Van Campenhout & Van Caneghem, 2009), without which commercial funding can still remain a nightmare. If these requirements are not met, it becomes difficult for the banks to ascertain the quality and quantity of information that the SME holds. Consequently, it poses further complications for lenders to separate between bankable (good) and doubtful projects and the pricing of loans under this scenario may result in inefficient selection of fund allocation.

Information asymmetry is aggravated by high levels of SME operational risk. SMEs often operate in very short period. Research by Duan et al. (2009) show that a quarter of small firms exit the market within a couple of years in operation while 52.7% disappear within half a decade due to bankruptcy, business failure, historic non-performing loans and other extenuating factors. With these alarming levels of SME mortality, it therefore becomes difficult for the SME to provide sound and substantial historic standardised financial statements when required during credit application. Issuance of loans in such circumstances increases the risks of banks substantially (Duan et al., 2009). The authors also observed that SMEs suffer more from credit rationing compared to large corporates due to their inferior position in transaction costs.

In China, Huang et al. (Huang et al., 2014) argued that difficulties in financing SMEs is due to information asymmetry. Limited finance continues to be the bottleneck restricting growth of SMEs globally. In Tunisia, Cote D'Ivoire, Mozambique and Kenya, SMEs perceive that unawareness of the availability of credit lines is one of the leading determinants of funding difficulties over and above lack of business support, lack of advice from the financial institution, complexity, cumbersome loan application process and inadequate collateral (Gana, 2013; Ghimire & Abo, 2013; Hezron & Hilario, 2016; Kiveu, 2015). These countries are located at the 4 geographical cardinal points of the continent implying that the problem of information asymmetry can be generalised to most African countries. The authors suggested that more social interactions, relationship lending whereby lenders develop a relationship or reach a common understanding with borrowers to enhance effective communication and ICT solutions could help curb lack of awareness of funding opportunities in Africa.

2.4 Stylised Facts about the SME Sector in South Africa

The SME segment is regarded an integral aspect of the economy in South Africa. The Department of Trade and Industry (DTI) developed and published the National Small Business Act (1996) wherein SMEs are defined across several economic industries for ease of funding and other forms of support by the public and private sectors. DTI is a government department which promotes structural transformation and economic development. In the Small Business

Act (1996), SMEs are segmented by revenue, gross asset value and size, with maximum thresholds of R40 million, R18million and 200 employees respectively (Appendix A). Empirical studies by Chimucheka and Rungani (2013) show that, SMEs in SA make up 90% of formal businesses, provide employment to about 60% of the labour force and total economic SME output accounts for roughly 34% of GDP. However, growth is inhibited due to various factors, the main one being the lack of access to funding.

The DTI (2008) reported on a comprehensive view of the SME sector in South Africa. The range in size of SMEs is very broad, covering registered to informal businesses. SMEs range from family businesses with a staff complement of about one hundred employees to micro-enterprises comprising survivalists and self-employed sole proprietors from the bottom end of the economy. The latter forms the majority of the SMEs in SA. These can take various forms including backyard manufacturing, street vending, home based evening jobs, among other informal forms of trade with little growth potential and minimum likelihood to afford employees. During the first quarter of 2008, a total number of 2 182 823 SMEs were reported (The DTI, 2008) across its nine provinces.

The South African government recognises the value of SMEs as evidenced by the establishment of the Ministry of Small Business Development in 2014 responsible for the facilitation of SMEs (SEDA, 2016). This department operates under various agencies. The Small Enterprise Development Agency (SEDA) implements SME business strategy. The Small Enterprise Finance Agency (SEFA), South African Micro-Finance Apex Fund (SAMAF) and Khula Enterprise Finance Limited provide funding requirements of less than or equal to R3 million (SEDA, 2016) through the provision of revolving loans, term loans, bridging finance among other governmental financial support streams. Technical support is provided through the National Youth Development Agency (NYDA) targeted for young population aged between 14 and 35 years. The National Empowerment Fund (NEF) too provides non-financial support to black owned SMEs.

Globally, SMEs evolve with economies, this too is expected for SME landscape in South Africa. SA has recently been characterised by major economic and political events. These include the 2008/2009 global financial crisis, a full cycle of interest rates (tightening to accommodative), a peak in commodity cycle (SEDA, 2016) and the changes in political administration from president Mbeki to president Zuma, followed by president Ramaphosa.

Accordingly, the SME sector is assumed to have adapted the new and evolving circumstances experienced by the economy. Despite the unparalleled government intervention and support, individual SME growth remained inhibited by various challenges at various scales depending on the size and scope. Commercial lenders are unlikely to fund young and informal businesses forming the greatest proportion of SMEs by volumes. SMEs in Gauteng are more likely to get funding compared to those in Mpumalanga and Northern Cape. This is primarily due to less sophisticated nature of the latter areas and a lack of access to infrastructure and a widening gap in technological divide. Skills shortage, permit delays and high levels of crime are some of the obstacles hampering SME growth across the country (SEDA, 2016). To gauge trends of SME performance in accordance with the major economic activities and other extenuating factors discussed above, summary statistics are provided below for the operating years 2008, 2015 and 2018, to accommodate changes seen over the decade.

Table 1: SME Distribution by Province (2008 vs 2015)

	Number (2008Q1)				Number (2015Q2)			
	Total	**Formal**	**Informal**	**Other**	**Total**	**Formal**	**Informal**	**Other**
	2 182 823	666 501	1 420 933	95 389	2 251 821	667 433	1 497 860	86 528
Western Cape	223 933	114 976	95 212	13 745	230 324	110 107	110 188	10 030
Eastern Cape	218 865	56 579	154 631	7 655	197 366	50 670	141 739	4 957
Northern Cape	29 894	11 450	11 768	6 676	20 611	8 534	9 058	3 019
Free State	114 949	31 040	76 127	7 783	96 846	26 224	60 816	9 806
KwaZulu-Natal	418 406	102 591	289 347	26 468	373 434	74 976	283 165	15 293
North West	109 860	25 817	76 855	7 188	112 856	27 430	79 153	6 273
Gauteng	687 556	270 093	405 180	12 283	785 321	306 231	465 100	13 989
Mpumalanga	193 259	29 760	156 814	6 685	185 399	35 208	141 129	9 063
Limpopo	186 101	24 193	155 001	6 907	249 663	28 054	207 512	14 098

Source (SEDA, 2016)

Table 1 shows that most SMEs operate in Gauteng followed by KwaZulu-Natal (KZN) and the least is in Northern Cape. During the period 2008 to 2015, SMEs in SA increased by a mere 3%, way less than the GDP growth of 14% over the observation period (SEDA, 2016). Limpopo and Gauteng SMEs grew by 34% and 14 % respectively while the Northern Cape numbers plummeted by a whopping 31% over the review period followed by Free State at 16%.

Table 2: SME Distribution by Economic Sector

	Number (2008Q1)	Number (2015Q2)				Turnover (2015Q1)	GDP (2015Q2)	Turnover /SME
	Total	**Total**	**Formal**	**Informal**	**Other**	**R million**	**R million**	**R million**
	2 182 823	2 251 821	667 433	1 497 860	86 528	2 908 020	815 636	1.29
Agriculture	87 820	56 774	0	0	56 774	n/a	35 213	n/a
Mining	2 696	2 199	0	2 199	0	35 256	69 421	16.03

Manufacturing	267 817	201 459	62 657	138 801	0	658 740	111 672	3.27
Electricity, gas & water	4 252	7 456	6 656	801	0	7 488	38 647	1
Construction	252 233	299 242	77 098	222 143	0	229 016	38 804	0.77
Trade & Accommodation	974 083	944 467	186 798	757 669	0	1 160 560	129 144	1.23
Transport & Communication	122 370	133 134	56 620	76 514	0	134 152	87 612	1.01
Finance & Bus. Services	236 740	271 712	172 423	99 289	0	571 384	183 430	2.1
Community	227 243	305 624	105 181	200 444	0	111 424	50 982	0.36
Other	7 569	29 754	0	0	29 754	0	70 711	0

Source (SEDA, 2016)

On a different dimension under the same review period, Table 2 shows that most SMEs operate in the domestic trade, recorded in Table 2 as Trade and Accommodation. This sector contributes the highest turnover in rand terms. However, GDP contribution is highly driven by Finance and business services and turnover per SME is mostly explained by the mining sector. Between 2008 and 2015, industries served shifted from a drop in Agriculture and Manufacturing and moved to Community and Construction. The latest trends show that SMEs continue to operate in Gauteng. In its latest report, SEDA (SEDA, 2019) indicated that 34.70% of South African SMEs are in Gauteng, followed by KZN at 16% then Limpopo at 12.30% as shown in the 2018Q3 distribution of SMEs in Table 3.

Table 3: SMEs Distribution by Province (2017-2018)

	2017Q3		**2018Q2**		**2018Q3**		**Quartely Change**		**Yearly Change**	
	Number	**Distr.**	**Number**	**Distr.**	**Number**	**Distr.**	**Number**	**%**	**Number**	**%**
Western Cape	268 821	11.90%	279 354	11.40%	260 439	10.20%	-18 915	-6.8%	-8 381	-3.10%
Eastern Cape	190 749	8.50%	215 334	8.80%	210 986	8.30%	-4 348	-2.00%	20 237	10.60%
Northern Cape	14 940	0.70%	19 690	0.80%	27 760	1.10%	8 070	41.00%	12 820	85.80%
Free State	110 291	4.90%	118 452	4.90%	101 709	4.00%	-16 744	-14.10%	-8 583	-7.80%
KwaZulu-Natal	325 051	14.40%	372 151	15.20%	400 967	15.70%	28 817	7.70%	75 917	23.40%
North West	125 329	5.60%	126 470	5.20%	125 046	4.90%	-1 423	-1.10%	-283	-0.20%
Gauteng	687 867	30.60%	808 598	33.10%	888 120	34.70%	79 522	9.80%	200 253	29.10%
Mpumalanga	216 328	9.60%	204 352	8.40%	226 230	8.80%	21 878	10.70%	9 902	4.60%
Limpopo	311 911	13.90%	296 359	12.10%	315 634	12.30%	19 275	6.50%	3 722	1.20%
	2 251 286	**100.00%**	**2 440 760**	**100.00%**	**2 556 891**	**100.00%**	**116 132**	**4.80%**	**305 605**	**13.60%**

Source (SEDA, 2019)

The number of SMEs in South Africa grew by 13.60% year on year from 2017Q3 to 2018Q3 driven by 29.1% growth in Gauteng and 23.40% growth in KZN. Negative growth was seen in the Free State, Western Cape and North West. The exploratory data analysis in this study will be used to determine whether these growth patterns align with the demand of credit in the respective provinces. As observed a decade ago in Table 1, the Northern Cape province still continue to trail behind in the volume of SMEs due to predominantly rural nature of the province, bearing the impact of technological divide and poor infrastructure.

SEDA (SEDA, 2019) reported that the relative market share of trade and accommodation sector contracted due to faster growth in other sectors such as community services, construction, financial & business services. On the other hand, the global economic slowdown poses a downside in domestic export demand, impacting negatively on trade. Turnover contracted across the sectors by 3.6% year on year up to the third quarter of 2018(SEDA, 2019) due to weak economic conditions. Eskom crisis has been a major risk due to load shedding, potential credit rating downgrade and pressure on the fiscus. The 2019 national budget showed deterioration in fiscal metrics due to Eskom and other State-Owned Enterprises (SOE) financial crises and downscaled growth forecasts. The real GDP for South Africa is estimated to grow by 1.3% in 2019 and 1.9% in 2020 (South African National Treasury, 2019).

2.5 Empirical Literature: SME Funding Determinants

SME funding determinants can be classed into environmental and internal factors. Environmental factors include government supported developments, industry & academic collaborations, financial resources as well as market dynamics. Internal factors are SME specific characteristics. Studies undertaken in literature show a combined view of these classes of determinants as discussed hereunder.

SMEs form an integral part of the economy as they are seen to be a suitable solution to cope with developmental issues such as high unemployment rate and poverty. In India, 30 million small firms contribute 45% of GDP although the funding gap of $126 billion has recently been recorded (Raghu & Pankaj, 2019). Most of these firms exist in the manufacturing industry and conform to the government's "Make in India" initiative to boost economic development and economic growth. By way of binary logit regression model, the authors established that financial feasibility and age of the principal owner are the most important drivers of credit extension. The sentiment on the market is that creditors need to lift loan sanctions at young age, improve the flow of credit to support innovation and rapid growth in this key sector. In Bangladesh, SMEs require financing for start-up capital, working capital and fixed capital. Poor access to capital due to lack of adequate collateral was observed to be a major constraint limiting SME growth (Ghate, 2000; Scholar & Chowdhury, 2017).

Many donor organizations and financial institutions have in the past stepped back from SME credit financing due to poor track record of such programs in developing countries. Institutional failure example is the lending program in Tunisia known as the Fonds de Promotion et de Décentralisation Industrielle (FOPRODI). The fund was set up in 1974 to promote and develop new industrial SMEs, decentralize the industry and encourage regional development (Bechri et al., 2001). Due to extremely low repayment rate, the program barely survived two decades and it finally collapsed in 1997.

The impetus for the creation of commercial banks is driven by business opportunities with a mandate to maximise profits and mitigate risk. Commercial banks consider SMEs high-risk entities which are costly to serve and therefore take a reluctant approach to finance them (IFC, 2010). The risk is often associated with poor financial records, management shortcomings, limited equity, lack of diversification and little experience. The World Bank Group (2018) added that, the main barriers to SME funding include macroeconomic volatility in developing countries and peer to peer competition in developed countries. As such, the proportion of SME lending in the aggregate bank credit portfolio ranges between 5 percent and 20 percent in developing countries such as Rwanda, Tanzania, South Africa, Kenya and Nigeria.

On a similar note, the bank-debt ratio of SMEs accounts for less than a quarter of SME total debt financing in Ghana (World Bank Group, 2018). The ratio is also positively correlated with firm size and tangibility of assets. SMEs ultimately resort to alternative sources of funding which tend to be more expensive, thereby hampering productivity, competitiveness, innovation and investments (IFC, 2010). Another issue identified in literature within the SME credit market is related lending. This occurs when banks issue loans to companies owned and controlled by bank officials at favourable concessionary lending rates. In Mexico, these loans were identified to default 33% more with a 30% less recovery rate than unrelated lending facilities (La Porta et al., 2003). As such, this is seen as a manifestation of looting.

Complications to funding by commercial banks in South Africa lie in the SMEs' failure to comply with financial regulations as required by the national credit regulators (Ayyagari & Beck, 2007). Financial lending institutions are bound by country specific as well as international legislation and regulatory barriers that potentially restrict SMEs access to commercial funding. South African credit lenders adhere to regulations such as the National Credit Act (NCA) and the Financial Intelligence Centre Act 38 (2001), FICA. The National

Credit Regulator (NCR) administers the provisions of the NCA across the credit lending industry.

The key feature of the NCA(2004) is to promote access to credit market and financial inclusion while deterring reckless lending. For example, through NCA, credit lending institutions are prohibited from conducting businesses with minors under the age of 18 unless there is strong motivation to override the directive. In addition to NCA regulations, FICA strongly enforces commercial banks to perform Customer Due Diligence (CDD) also known as Know Your Customer (KYC) process. This entails gathering high quality and usable information within acceptable quantities on credit recipients prior to the extension of credit to curb information asymmetry and circumvent financial crimes. FICA regulation adheres to the international Financial Action Task Force (FATF) whose main objective is to fight illicit financial flows such as terrorism financing and money laundering.

2.6 Remedial Actions and Alternative Sources of Finance

As part of the remedial actions, Binswanger & van den Brink (2005) proposed client diversification in the funders' portfolio in order to contain covariant risk. Further, lenders were strongly recommended to isolate themselves from the state and opportunistic behaviours. On the other hand, borrowers were encouraged to take up insurance cover to guard against any potential idiosyncratic and systemic risks. Lieno (2014) recommended an improvement in bank models to adapt specialised services for small businesses by establishing processes to handle the extensive file processes in accordance with the legal and judicial framework.

Microfinance Institutions (MFI) form an alternative source of funding by offering micro loans to borrowers who are unable to access conventional loan services. MFIs' key business purpose is lending to SMEs (Jarotschkin, 2013). To improve the performance of SMEs, MFIs recently established SME specific product called meso-finance to meet the financial needs of entities above the microfinance level and below the commercial financial needs (Lieno, 2014). Another attractive feature of MFIs is the establishment of joint liability schemes whereby loans are issued at group level, rather than individual.

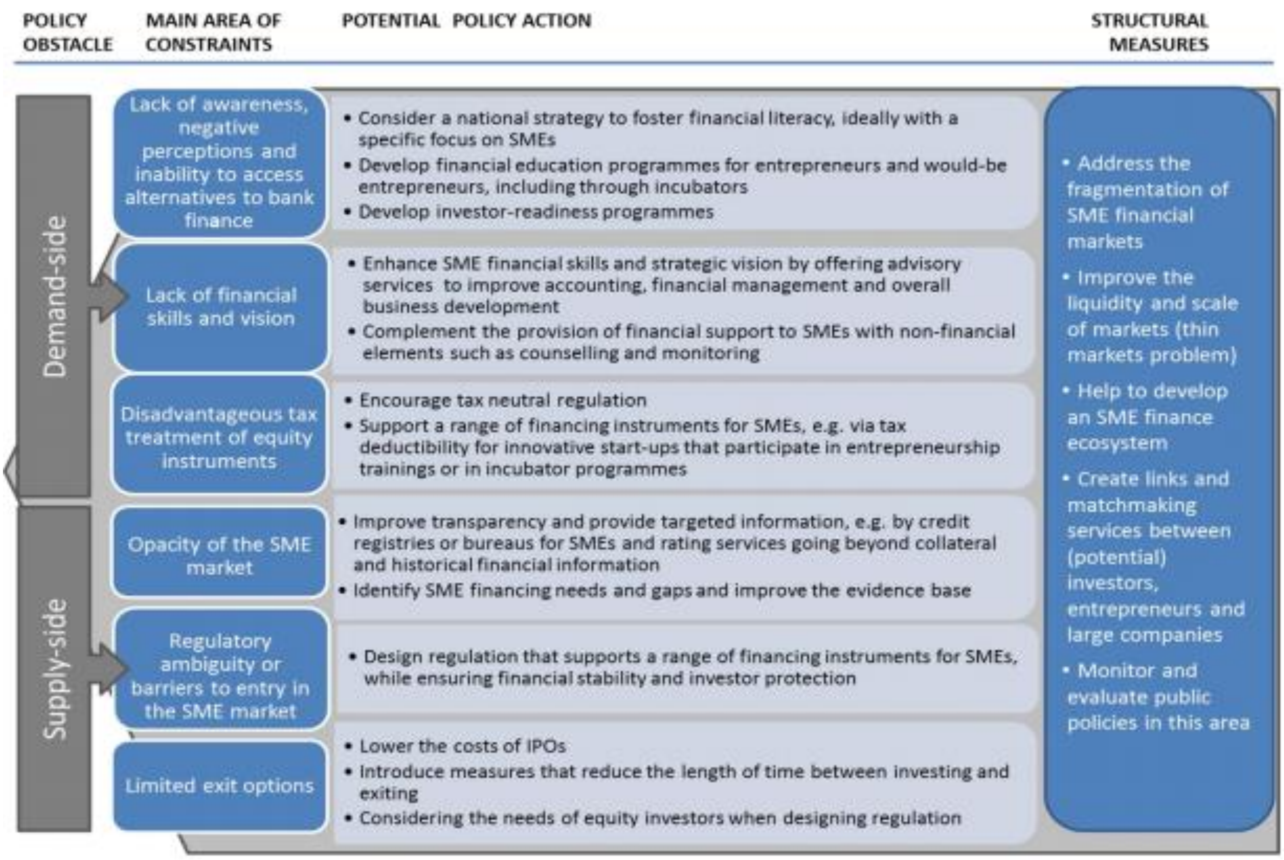
Joint liability enables lenders to collect more information on borrowers thereby reducing the risk of AI and moral hazards (Binswanger & van den Brink, 2005). In line with various authors' sentiments, group lending is often associated with incentives such as short maturities, increased loan amounts, personalized repayment schedules and forced savings: (Binswanger & van den Brink, 2005; Garmaise & Natividad, 2013; Ghate, 2000; Lieno, 2014; Morvant, 2007; Yaron & Manos, 2007). Examples of MFI as per the Forbes (2010) article are: the Grameen Bank in Bangladesh, Consumer Credit Union 'Economic Partnership' in Russia, Enda inter-arabe in Tunisia and Asmitha Microfin Ltd. In India.

Venture Capital (VC) is another form of SME financing. VC structures provide equity rather than debt and thereby lowers the debt to equity ratio for high risk entities. Further, VC set up enables the fund suppliers a share in the funded business an opportunity to be actively involved in business operations to protect their interest (Kitchen, 1989). Furthermore, bank affiliated VCs play a crucial role in promoting relationship lending and mitigating AIs that are detrimental to SME lending (Konishi & Suzuki, 2007) by being the nexus strengthening ties between SMEs and commercial banks. The authors observed that in Japan, over the period 1996 to 2000, more than 50% of the top 100 VCs were subsidiaries of commercial banks. They concluded that commercial banks investment via VC subsidiaries benefit SMEs by increasing credit availability and in turn reducing borrowing costs.

There has been notable efforts across the globe developed to enhance vibrant entrepreneurial culture using non-bank service provision through financial and non-financial support. Risky capital can be financed through non-bank lending programs. Hometown Investment Trust funds (HIT) offer financial intermediation between lenders and borrowers who know each other and are often project driven, lenders can choose to invest in specific projects. HIT has recently been adopted as a national strategy in Japan. In Thailand, the Market for Alternative Investment finances SMEs through capital markets (Yoshino & Taghizadeh Hesary, 2014).

Non-bank programs enable SMEs to access stable funding, enhance sustainable growth, enforce transparency and good governance, alleviate AI issues and promote powerful networking. On the South African SME market, SEDA support structures range from conceptualisation to expansion phases of SMEs with close involvement in training, business registrations and business planning. Nonetheless, non-bank support services are also characterised by challenges, some of which are listed in Figure 3 with recommended demand/supply side policy responses aligned.

Figure 3: Challenges and Policy Responses to Non-Bank Lending Programs



Source (OECD, 2018)

2.7 Information and SME Lending

The success of the SME credit market is largely dependent on the ability of the lending practitioners and researchers to extract meaningful information needed to identify the key performance indicators (Page, 2016). As such, it is essential to establish systems that capture the right data which can easily be usable by the lending entity. The data should be set up in well defined auditable processes under strict discipline to ensure authenticity, transparency and accuracy. In developing countries, the lack of SME credit rating scheme has been a challenge for the SME credit market (Yoshino et al., 2015). SMEs are characterised by unstable financial structures as some business activities are seasonal, some are opaque and new start up enterprises lack credit history. The increased AI enforces banks to increase interest rates to contain the risk of default.

The motivation for developing SME credit bureau database is to shield banks from risky lending and reduce borrowing costs for less risky SMEs. For Thailand, Yoshino et al.(2015) suggested a way to generate a credit risk scheme for small businesses in the absence of authentic SME financial records. However, the analysis was based on the National Credit Bureau (NCB) of Thailand from where the authors made use of the loan amounts and repayment behaviour of SMEs available on the NCB. The scheme was developed using statistical approaches such as Cluster Analysis and Principal Component Analysis (PCA). This approach may not work for African countries due to lack of credit bureau databases for SMEs.

Moody's, a financial services company and a top credit rating agency, developed RiskCalc, a database for private companies which incorporates market information and SME historical performance on credit facilities on a global scale (Page, 2016). According to the author, this information can be used by lenders within the credit lending space in generating effective triggers for early warning detection against credit deterioration on SMEs. OECD (2018) on the other hand, recently introduced OECD SCOREBOARD, a database created to capture SME data as a way to reduce AI and improve the SME credit market.

In most SME credit market research studies, authors developed an understanding of the credit market using either demand/supply side survey data as well as the national/international information. The literature indicates that most of the information has been primary or secondary cross-sectional data organised in a panel form (Beck et al., 2008; Chimucheka & Rungani, 2013; Cusmano, 2015; Fatoki & Garwe, 2010; Levy, 1993; Mutezo, 2015; OECD, 2018; Page, 2016; Schmukler & Abraham, 2017; Yoshino et al., 2015).

This study proposes the use of longitudinal data from a single high ranked financial institution in South Africa. The analysis will be done on a cohort basis using novel statistical approaches that have recently been adopted in the banking sector to model credit risk within retail credit portfolios (Jilek, 2008). Loan applications will be tracked for each calendar month over a period of seven years. Due to the lack of SME specific bureau database in SA, the credit performance of the principal account holder of each SME will be used as a proxy. In addition, the macroeconomic information will be considered over the review period. The use of internal and external longitudinal data contributes increased volumes of data and enhances stability and robustness of the resulting models.

2.8 Demand and Supply of SME Credit Market

The condition of smallness either by design or by default as described in Section 1.1 results in some micro enterprises having equity finance as their greater portion of their capital structure compared to other streams of finance such as debt (Anderson & Ullah, 2014). Perennial SME infants tend to reinvest profits and by all means possible avoid taking debt and therefore lack the drive to demand credit, even financial liberalisation has little impact in such instances (Aryeetey et al., 1994). The authors, on the back of their surveys conducted in Ghana, assert that, highly profitable opportunities could be missed due to lack of willingness to access external funding on the part of these microenterprises. On the other hand, banks have shown little interest in developing SME market niche due to lack of bankable demands (Aryeetey et al., 1994). Therefore, the smaller the firm, the lower the demand and supply of SME credit.

After the 2007 Eurozone financial crisis, the real economic activity declined in most parts of the world. This has been reflected in increases in government bond yields. The enormous credit expansion experienced prior to the credit crunch led to large debt overhang which is a measure of debt to output in private firms (Holton et al., 2012). On the back of the crisis, lending to the private sector drastically plummeted. The actual drivers of this decrease have been debatable over time. Some researchers identified weak demand on the part of the firms (Campello et al., 2010) whilst others alluded to the tightening of the credit conditions on the lenders part having contributed to lower aggregate lending (Jiménez et al., 2012; Puri et al., 2011).

In as much as the decline in the lending trends has been observed to be associated with firm and lenders behaviours, Holton, Lawless, & McCann (2012) argued that, macroeconomic factors following the crisis led to changes in SME credit market. The authors performed a panel study on 24 000 SMEs across 11 economies during the period 2009 to 2010 and concluded that the economic growth rate as reflected by the real GDP, and the debt overhang on the part of the firms are the significant drivers of the demand for SME credit.

The weaker the economy, the lower the demand for credit. Sovereign and financial factors reflected in sovereign bond yields and the median CDS spread respectively, affect the lenders funding positions (Holton et al., 2012). These were observed to impact negatively on SME credit supply. Thus, at SME financing level, weak macroeconomic factors can inhibit demand and supply of SME credit (Holton et al., 2012).

2.9 Credit Scoring

Regulatory and legislative requirements discussed in Section 2.4 are only a component in the process of granting loans. Another critical step in credit assessment is to evaluate creditworthiness of applicants. The applications undergo credit scoring process where ratings are assigned to determine their ability to repay debt timely and in full. Credit scoring refers to customer creditworthiness rating and it forms the cornerstone of credit risk management. This is divided into two main pillars: the front end (acquisition) and the back end (existing customer). Front end deals with through the door customers where application scorecard contributes to credit lending decision process.

Before issuance of loans, commercial banks assess applicants to determine their creditworthiness. The application scorecard becomes an important aspect for business acquisitions. Back end process uses behavioural scorecard to determine risk levels of existing customers and inform credit risk management and collection strategies. To enhance the acquisition process, an application scorecard is developed in this study. The quantitative analytics component of this study delves into the empirical customer application and performance data to determine the main risk drivers and establish factors that lead to loan application rejections. Financial providers develop scorecards using historic data with an assumption that the historic trends are like future experiences.

2.10 Statistical Approaches to Modelling Credit Risk

Conventional statistical approaches were used to model risk in the past (Capon, 1982). Notably, the initial methodologies of significance, which gained popularity for being theoretically straightforward include linear regression and discriminant analysis. However, the data fell short in assumptions required for these approaches. Consumer credit data are often associated with non-constant variance, a condition known as heteroscedasticity because the response variable is normally binomial that indicates whether or not a loan or facility will default (Jilek, 2008). To curb inaccuracies associated with violation of principal linear regression assumptions, most financial institutions adopted a binary response variable type of regression known as logistic regression. The scoring function in logistic regression is the probability of default and this feature makes it attractive. Logistic regression the model is expressed as follows:

$$p(Y_i) = \frac{e^{\beta_0 + \sum_{i=1}^{n} \beta_i X_i}}{1 + e^{\beta_0 + \sum_{i=1}^{n} \beta_i X_i}}$$

Where Y_i is the binary response variable, X_i is a vector of independent variables with their associated parameter estimates β_i and e is the natural logarithm. What makes logistic regression attractive is that the exponential function is always non-negative and the probability values are restricted within [0, 1] range (Lottes et al., 1996). Thus, this study employs logistic regression technique to build the application scorecard of SMEs.

2.11 SME Application Scorecard Development

During the mid-1990s, Fair Isaac and Company, a data analytics company based in California developed one of the first application scorecards bespoke to SMEs (Harvey, 2006). The author noted that this was adopted by most of the United States (US) and the United Kingdom (UK) banks to implement credit scoring for SMEs within their economies. The use of pooled data (where data comes from multiple lenders) in formulating SME scorecards proved to be a success in terms of cost effectiveness, improved bad debt management and regulatory compliance on the back of enhanced risk control in the developed world. On the other hand, the developing market still rely on: the use of proxies or benchmark scorecards whereby a scorecard developed for the retail/corporate credit market for instance can be applied to the SME credit market, expert judgements where the decision to accept or reject an application is based on experience, the use of financial statements and 5C's of credit which SMEs lack in most and can also be subjective (Caire, 2009).

Drawing on learnings from the developed world, this study adopts a similar approach by developing an application scorecard bespoke to SMEs in an emerging market context but from a single money lending financial institution. For the purposes of this study, pooled data from different entities may not be accessible due to the bureaucratic nature of the businesses. However, since the institution in scope is one of the four leading banks in South Africa, the assumption is that similar trends are to be expected across the industry. The development of a scorecard tailor made for SMEs enables the lenders to quantify the risk associated with SME loan applicants, improves on objective decision-making processes and reduces transaction costs as seen in the developed world as highlighted in literature.

2.12 Empirical Studies: SME Access to Finance

Firm-financing gap is a term used to describe the inadequate access to finance faced by SMEs (IFC, 2010; OECD, 2018; Schmukler & Abraham, 2017). This gap has been observed to be an obstacle to the growth of firms as it inhibits innovation, research and development (Fowowe, 2017). On 26 African countries examined, limited finance is the top SME growth inhibitors ahead of inadequate infrastructure, intermittent electricity supply, corruption, labour regulations and macroeconomic instability, among other factors (Gelb et al., 2007). In the Caribbean, lack of access to finance is the third highest inhibitor to SME growth (Dinh et al., 2012) whereas this factor is ranked the highest in 38 Sub-Saharan countries sampled.

Firm-financing gap is dominant due to severely disadvantaged financial system architecture in developing countries (Beck, 2013; Fowowe, 2017; Keskin et al., 2010). SMEs lack access to equity markets and it is often difficult for them to access public debt (Beck, 2013). This is a supply side problem also identified by Kamau (KAMAU, 2015) whose empirical research on Kenya's SMEs pointed out the problem of financial exclusion and lack of sensitivity to SMEs by financial institutions. Empirical research by Thorsten Beck (Beck, 2007) in developing countries shows that weaknesses in financial systems, high levels of transaction costs, stringent regulatory framework and difficulties in risk management make commercial banks very reluctant to reach out to SMEs. The author recommended market friendly activist policies, government backed institutional building and more reasonable regulatory environment enabling banks to grant SME financing with ease.

Haritone (Haritone, 2016) undertook a census of 43 commercial banking institutions in Kenya, implored their annual, audited financial reports over a period of 5 years (2010 - 2014). Using multiple linear regression, the author concluded that the bank size and liquidity status significantly impacted on lending capability to SMEs. Interest rates and credit risk played no significant role in SME credit lending. By implementing policies to grow commercial banks, lending to SMEs can be improved. On a similar note macroeconomic indicators such as financial deepening, commercial bank's total assets, inflation, are contributing factors to the lack of SME funding in Nigeria (Adeyeye et al., 2016). Njeru Njue & Mbogo (Njeru Njue & Mbogo, 2017) sampled 17 of 46 commercial banks in Kenya and conducted in-depth research on SME access to commercial bank finance. The authors concluded that factors hindering SME access to finance include lack of creditworthiness information on small firms, low net worth of the applicants as reflected in their low value balance sheets, lack of collateral and information asymmetry. Essentially SMEs mostly failed to satisfy the 5Cs of credit (Collateral, Character, Capital, Capacity and Conditions). The authors proposed resolutions to these issues through advancing financial literacy to applicants, development of credit scoring systems compliant to credit bureau regulations and improvement in truthfulness and honesty on the part of SMEs.

Kira (Kira, 2013), based on their assessment on 164 SMES from Tanzania, argues that SME management's education, firm's location, industry, size of business, incorporation, age and collateral availability are some of the noticeable factors affecting access to funding. The author recommends firm managers to acquire business skills to enable them to adjust to financial institutions requirements for funding. Further, they made some recommendations to the government to create a suitable environment for SMEs to operate through strategic planning, training, education and implementation of SME support sector.

Binswanger & van den Brink (2005) conducted a detailed research in the agricultural sector SME financing in Africa and identified the main problems faced by the lenders as: seasonality in the agricultural chain from farming to market, covariant risks (common shocks due to weather patterns, pest infection or prices), information asymmetry, arising from the differences between the quality and quantity of information shared among stakeholders, moral hazards occurring when the funding is not utilised for its intended purpose and political pressure enforcing lenders to restructure or forgive agricultural debts. Levy (1993), on the back of their field surveys in Tanzania's furniture industry, identified SME growth inhibiting factors arising from the comprehensive enforcement of regulatory and tax policies and the bureaucratic burden of negotiating with the government. Even adequately sized and experienced firms faced the same predicament but with less difficulties than SMEs.

A study on Latin American firms showed that internal factors such as firm size, technological advancements and formality are the most important affecting the ability of SMEs to access finance (Alberto & Peñaloza, 2015). These factors play a crucial role in harnessing the competitive advantage of the firms resulting in improved cash flows and other aspects motivating commercial lenders to grant loans. Commercial banks' loan officers in Spain argue that the firm's audited financial reports results in better willingness of the lenders to grant them credit (Palazuelos & Crespo, 2017). Coupled with the general perception of audited reports was competence and honesty. Benevolence was not seen as a contributing factor to loan access.

The SME sector in South Africa is dominated by slow growth businesses and a lack of funding is the major constraint towards further development (Mutezo, 2015). Some businesses die at infancy due to lack of financial support. In fact, commercial banks are sceptical to fund SMEs due to their specialised mandate. Owing to the intensely diversified and opaque nature of SMEs, a huge number of credit applications are turned down because of their inability to satisfy NCA and FICA requirements. These regulations are observed to be the major hindrances to access commercial funding by SMEs ahead of behavioural and risk assessment attributes (Beck et al., 2008). On the other hand, Mutezo (2015) argues that technological divide, information asymmetry and failure to meet regulatory requirements are the major reasons commercial banks reject SME applications for funding.

2.13 Summary

This Chapter reviewed the importance of SMEs, successes and pitfalls experienced in this sector, particularly in the context of SME credit landscape, from both the demand and supply perspective. Globally, SMEs are touted as engines of economic growth. They span a wide spectrum of economic sectors and are inclined to foster innovative entrepreneurship and gratify a variety of socio-economic objectives such as poverty alleviation, generation of income, employment creation, economic growth and reduction in societal inequalities. These economic sectors include agriculture, mining, construction, trade, transport, communication and manufacturing, among others. SME output accounts for a sizeable portion of the GDP depending on the global classification of the economy.

In South Africa, SME sector is supported by its government through an array of agencies was established to facilitate, promote and develop small enterprises. These include, but not limited to SEDA, SEFA, SAMAF and NYDA, among others. Despite the unmerited government intervention on this part of the globe, SME growth has been hampered by lack of access to commercial funding. Start-ups and informal businesses form the greatest proportion of SMEs in the country and lenders are less likely to grant them loans due lack of credit history and information asymmetry. Studies show that SMEs in Gauteng are more likely to get funding compared the predominantly rural Mpumalanga and Northern Cape due to a lack of access to physical infrastructure and widening technological divide. Skills shortage, permit delays and high levels of crime are some of the obstacles impeding SME growth across the country.

From the supply side of the SME credit landscape in South Africa, the Chapter explored the theoretical credit scoring techniques supported by the empirical literature. Potential drivers of lack of SME funding were discussed based on previous studies. This section further discussed application scorecard development and the statistical approaches to modelling credit risk, in line with SME credit industry.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This study seeks to identify macroprudential indicators and macroeconomic factors influencing the demand and supply of credit in the South African SME sector. The investigation made use of information obtained from one of the leading commercial banking institutions in South Africa. Using the dataset in scope, an empirical evaluation was conducted through exploratory data analysis and statistical inference. Quantitative approaches were used to determine the drivers of risk and SME behaviours leading to default. This Chapter discusses the methodologies in detail.

3.2 Data Sources

Research data was obtained from one of the leading banks in South Africa. From the main data warehouse, the application, behavioural and performance information on SMEs were extracted and insights were drawn from the empirical data. Bureau data, macroeconomic information and credit industry data were sourced from the external institutions, Experian and Moody's, for each month in observation.

3.3 Population, Sampling Approach and Sample Size

This study considered all application information available on SME applicants within the overdraft facility over a seven-year period from July 2012 to July 2019. For the purposes of time series analysis, this study considered each month in observation, totalling 85 data points. At each point, volumes of applications received were flagged as the demand of credit whereas the size of the approved loans reflected the supply of credit by the lender. The actual figures corresponding to these trends are provided in Chapter Four.

For the SME application scorecard model development, cohorts of applications received in each month in observation were tracked to determine the behaviour of applicants over time. The sample size was determined by the total number of OD applications submitted to the bank by SME applicants during the seven-year period specified above. The actual numbers in each category described above are provided in the population flow in section 3.6.4.

3.4 Demand and Supply of SME Credit

Demand for credit was determined as the volume/number of applications received from SMEs while supply of credit is the acceptance rate (accepted applications/total applications) of the applications in each month. The macroeconomic indicators are economic growth (GDP) and prime lending rate (PLR) while the macroprudential indicators; overdrafts and loans (OL); disposable household income (DHI), debt service ratio (DSR) and credit extended to households (CEH) were employed as control variables. The relationship between and macroprudential indicators, macroeconomic factors, demand and supply of SME credit is depicted by the time series linear regression as;

$$D_{cred_t} = \beta_0 + \beta_1 GDPG_t + \beta_2 PLR_t + \beta_3 DSR_t + \beta_4 OL_t + \beta_5 DHI_t + \beta_6 CEH_t + \epsilon_t \text{ ....1}$$

$$S_{cred_t} = \beta_0 + \beta_1 GDPG_t + \beta_2 PLR_t + \beta_3 DSR_t + \beta_4 OL_t + \beta_5 DHI_t + \beta_6 CEH_t + \epsilon_t \text{ ....2}$$

where D_{cred_t} and S_{cred_t} denotes monthly aggregate demand and supply of credit by SMEs and t is time in months. The measurement and description of the variables in demand and supply of credit equations are presented in Table 4.

Table 4: Macroeconomic Indicators

Macroeconomic Factors	
GDP Growth (GDP)	Annual (year on year) growth rate of the Gross Domestic Product (GDP) based on the local currency. "GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products", (World Bank Group, 2018).
Prime Lending Rate (PLR)	Actual PLR values representing the lending rate expected to meet the short needs of businesses. PLR can be defined based on the objectives of financing and creditworthiness of borrowers.
Macroprudential Indicators	
Debt Service Ratio (DSR)	Debt service amount as a fraction of total debt. "Total debt service is the summation of principal repayments and interest paid in currency, goods, or services" (The World Bank, 2018).
Overdrafts and Loans (OL)	Annual growth rate of credit provided to the private sector by financial corporations through overdraft facilities and other loan types such as term loans, vehicle finance, credit card and mortgages.

Disposable Household Income (DHI)	Year on year growth rate. DHI Measures total net income received by households through wages, salaries and enterprises among other income streams after considering taxes and other contributions.
Credit Extended to Households (CEH)	Annual growth rate of credit provided to households by financial corporations through the retail lending facilities such as personal loans, term loans, revolving facilities, clothing and instalment debt, among other loan types.

3.5 Time Series Diagnostics

3.5.1 Unit Root Analysis

The time series regression analysis is based on the stationarity assumption of the series of macroeconomic factors and macroprudential indicators considered in this study. Non stationarity in the input series leads to spurious ordinary least squares (OLS) outcome, hence the need to test for stationarity in each of the variables in scope. Required is the determination of order of integration that achieves stationarity of each of the variable. This can be attained by unit root testing of the respective series. Non stationarity implies the existence of unit root. In this study, the Augmented Dicky Fuller [ADF] test was used to test for stationarity and determine the order of integration. It involves estimation of the following regression equation [with intercept and trend]. Differentials and time lags are added until stationarity is achieved (Dufour & Renault, 2019).

For time series X;

$$\Delta X_t = a_0 + a_1 t + a_2 \Delta X_{t-1} + a_3 \Delta X_{t-3} + \cdots + a_n \Delta X_{t-n}$$

Where X_t is the series of a macroeconomic indicator at time t and Δ indicates the differencing operator. The null hypothesis suggests the existence of a unit root while the alternative hypothesis represents stationarity.

3.5.2 Cointegration Analysis

Following on the stationarity tests, if integration of at least order one is observed in the macroeconomic indicators, it is imperative to establish whether there exists a linear combination of the series of interest, exhibiting stationarity in levels and differentials of the ensuing series. It was observed in this study that the all the series are stationary of at most order one (I(1)). This warrants the use of the Johansen's cointegration test to establish the existence of cointegration among the series in scope or the absence thereof. This test is suitable for use when the series of interest are integrated of the same order (Malik & Velan, 2019; Tiwari, 2012; Wickremasinghe, 2011). The Johansen test provides estimates of all possible cointegrating vectors through transformation of data into eigenvalues. The null hypothesis suggests no cointegration and the alternative relates to the existence of cointegration. The presence of cointegration indicates long run relationship which implies the existence of a short run disequilibrium. This can be corrected in the long run through a vector autocorrection term (Malik & Velan, 2019).

The Johansen cointegration test indicated no cointegration of the series in scope in this study. As such, the unrestricted Vector Autoregression (VAR) model was therefore used to establish the linear interdependencies among the multiple time series and their differentials. VAR is a stochastic process that generalises the univariate autoregressive model to a vector of macroeconomic series (Chowdhury, 1986; Markku & Pentti, 2013). This was performed for both demand and supply aspects of the analysis. The results are provided in Chapter Four.

3.6 SME Application Scorecard

The relevant information was extracted from the data warehouse of the institution in scope. This entails information on SMEs who submitted applications during the observation period for an overdraft facility in scope. The raw dataset consists of standard variables which cannot be modelled on but are crucial as identifiers and important indicators for the purposes of segmentation. Standard variables include, inter alia, ID number, observation month and account number. Sensitive information such as ID number and account number were masked to comply with issues of confidentiality in the business environment. Table 5 shows a sample of variables considered standard in this study, their description and usage.

Table 5: Standard Variables

Variable	Description	Usage
ID Number (masked)	Unique identifier of the principal account holder	Age of the principal account holder can be derived from this variable.
Account Number (masked)	Unique identifier of the loan facility	To link performance tables and track the behaviour of the loan over time

Month	Month of loan application	Segmentation and analysis by application cohorts
Reason for rejection	An indicator with code, stating the reason for rejection for all applicants failing to meet the loan granting criteria.	To determine the volumes of accounts rejected due to regulatory requirements as a percentage of total applications

3.6.1 Measuring Default Status

The South African banking industry adheres to the international banking regulations recommended by the Basel Committee on Banking Supervision (BCBS) through the Basel Accords. For the local banks to sustain adequate capital reserves, the Basel Accords are enforced by the South African Reserve Bank (SARB) to ensure sustainability in the event of economic strain. This study therefore follows the default definition as defined in the Basel Accords (Bank for International Settlements, 2012) as follows:

"A default is considered to have occurred regarding a particular borrower when either or both of the two following events have taken place.

- The bank considers that the obligor is unlikely to repay his/her credit obligations to the bank in full.
- The obligor is more than 90 days past the due date on any credit obligation to the banking group."

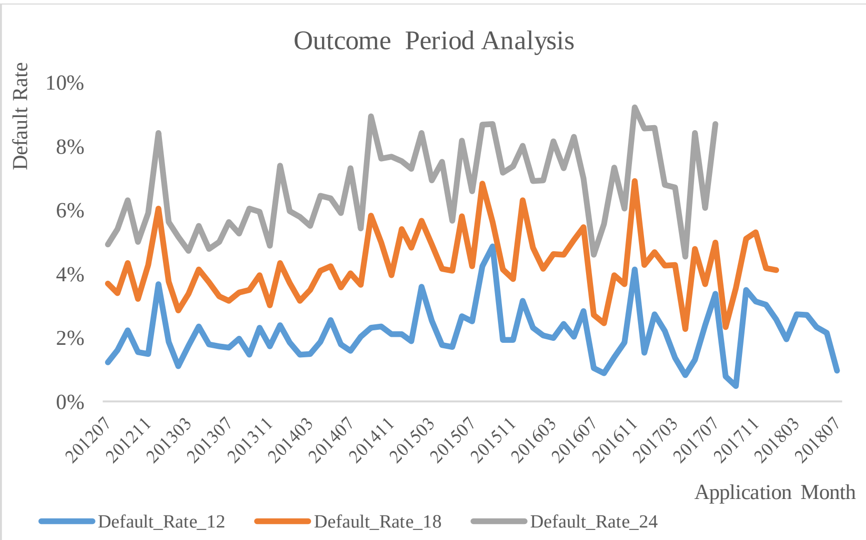
This definition of default was be used to derive the default status, the dependent or response variable in the application scorecard model building process.

3.6.2 Outcome Period Analysis

When employing the binary target logistic regression statistical approach, sufficient time is sought to track performance of loans between the loan activation point to the point of default. The performance or outcome period is determined on a cohort basis. Using the full information provided on the commercial lenders' portfolio, the loan repayment behaviour of cohorts or a set of customers whose applications were approved and activated in the same month were tracked. This is done to determine the average amount of time it takes for the customers who eventually default to realise the event. This period is referred to as the performance period or the outcome period in this study. This period is chosen in order to maintain relevancy of the model to current experience whilst ensuring adequate observations to be made for development to enhance stability of parameters. In practise, the performance period is normally set between 12 to 24 months (Siddiqi, 2006), depending on the structure of the data. An empirical analysis was conducted in this study to determine the performance period which suits the data in scope.

The default definition described in Section 3.6.1 was used to identify and reflect the difference between good and bad cases. The "bad" and "good" categories refer to whether a credit default event occurs or not, respectively, over the performance window. Using the historical subpopulation of the accepts, cohorts of applications were tracked from the application month over various periods to capture the volumes of the good and the badly performing accounts at each horizon. The forecasting horizon is consistent with the Basel Accords, which explicitly requires financial institutions to use longer time horizons (in excess of 12 months) in rating assessments (BCBS, 2017). Figure 4 shows the trend at 6 months horizon intervals from 12 to 24 months. It is imperative to determine the outcome period with a view to maintain relevancy of the model to current experience whilst ensuring a enough observations for the stability of the input variables. As expected, the default rate (bad rate) increases with an increase in the horizon. It can be observed that most defaults occurred in January 2013 and October 2016 cohorts consistently across horizons.

Figure 4: Outcome Period Analysis



Source: Estimates from research data, 2019

Based on the trends provided in Figure 4 and the corresponding summary statistics in Table 6, it was noted that the 18 months period was the most conservative trade-off between stability and reactiveness of the model. Table 6 indicates the number of bad accounts for different outcome periods on the entire SME Overdraft portfolio over the observation period. The 12 months horizon is the most stable but with the lowest number of bads which may lead to a low statistical significance of the model. The 18 months horizon has more bads with a lower standard deviation than the 24 months outcome. Even though the 24 months horizon has the most bads, the period maybe too long to observe performance and relevancy is likely to be lost. For these reasons, an 18 months outcome period was chosen.

Table 6: Outcome Period Analysis

Time on book (Horizon)	Total number of Applications	Total number of Bads	Mean (Average Bad Rate)	Standard Deviation (Volatility)
12 months	43,428	891	2.13%	0.00822
18 months	41,007	1,701	4.25%	0.01001
24 months	38,632	2,521	6.70%	0.01307

Source: Estimates from research data, 2019

3.6.3 Definition of Variables

Independent variables were extracted from the application tables found on the data warehouse. For the previously accepted applications, the repayment behaviour was tracked in order to establish a link between application variables and default. Additional variables were derived from the readily available raw data if they were deemed to be predictive of loan performance. Potential risk drivers and other behavioural variables which can be used as predictors of risk are in Table 7. Some are raw variables extracted from the data warehouse and some are derived.

Table 7: Potential Risk Drivers

Variable	Description	Rationale for Consideration
Default Status	A derived binary target variable indicating whether an account defaulted within the outcome period	Binary target variable
Time since last transaction	The time that has elapsed (in months) since the applicants' last credit transaction on their main account with the lender	The higher the number of months since an applicant's last credit transaction, the greater the likelihood of the applicant not having sufficient funds to meet debt obligations and thus the higher the risk of default.

Sector	The industry under which the applicant operates is indicated by this variable	Certain industries tend to be riskier than others and will be allocated comparatively lower scorecard points.
Number of Credit Enquiries	The number of enquiries made by the principal business owner in the last 12 months	Applicants who have made a large number of enquiries in a short period are considered risky and will be allocated low scorecard points.
Time since payment profile	The time that has elapsed (in days) since the principal business owner opened a payment profile	Applicants who acquired their latest payment profile further in the past tend to be less risk than those who have acquired it more recently.
Worst Arrears Recent	The Worst Arrears in the Last 6 Months by the principal business owner	The worse the arrears level in the past 6 months the greater the risk of default and the lower the scorecard points to be allocated
Worst Arrears Ever	This variable reflects the worst arrears level in the entire credit history of the principal business owner.	The worse the arrears levels in the principal business owner's credit history, the greater the risk of default and thus, the lower scorecard points to be allocated.
Guinness Rating	This variable is based on a set of matrices including Turnover, Time with the lender and time in business.	Applicants who have a low Guinness Rating tend to have a high default risk and will be allocated low scorecard points.
Time with Lender	The period of time (in months) an applicant has been a client of the lender	Applicants who have been the lender's clients for a longer time period are perceived to have a low default risk.
Excess	Business Entity Excess Indicator	Business entities which have never been in excess are perceived to have a low default risk and will be awarded high scorecard points.
Worst Excess	Principal business owner Worst Excess	Principal business owners who have never been in excess are perceived to have a low default risk and will be awarded high scorecard points
Worst Report	This variable represents the principal business owner's worst credit bureau report	The worse the principal's credit bureau report, the higher the risk of default and thus, the lower the scorecard points to be allocated.

These variables were explored to derive insights and structure of SMEs who seek commercial funding. It is of paramount importance to understand the reason for application of the loan. It is expected that the loan requirement arises due to the need to cater for increases in operational costs and to improve growth of businesses.

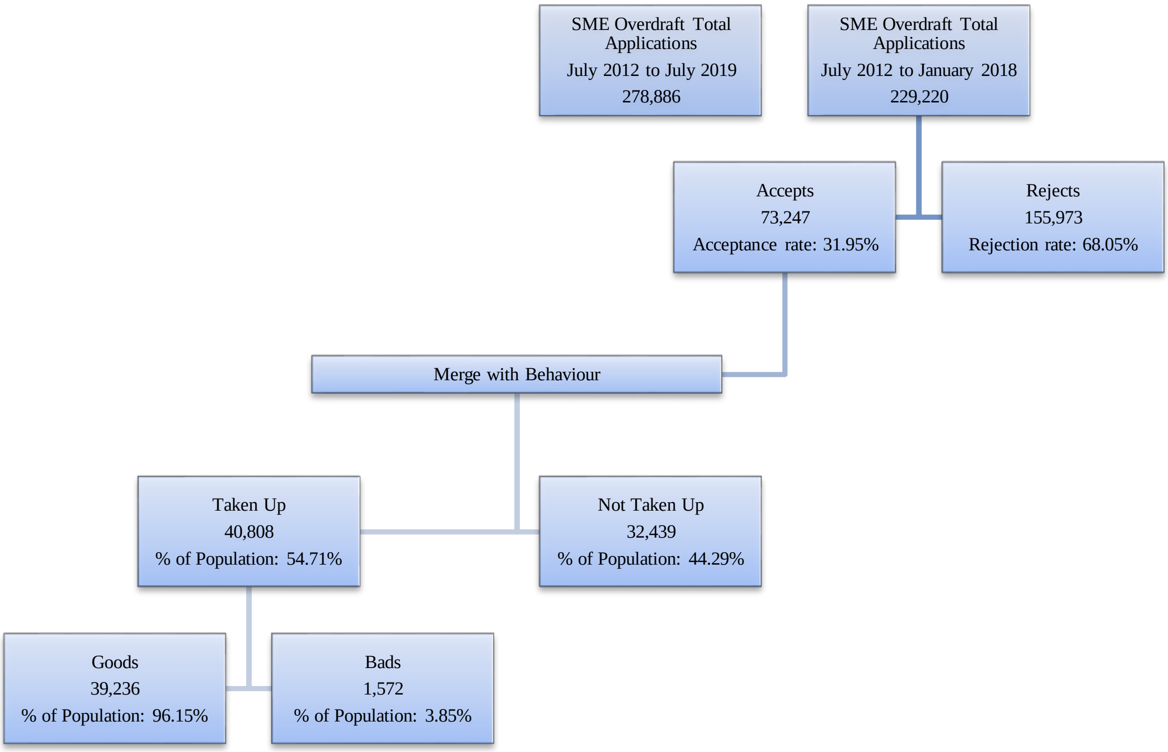
Every variable eligible for use in modelling needs to be assessed for validity, authenticity and relevance within context. For each variable the proportion of the missing values needs to be less than or equal to 15 percent unless the missingness can be motivated by reasonable arguments (Marimo & Chimedza, 2017). In a typical consumer credit data set, ordinal, continuous and nominal variables exist. For the purpose of scorecard development, often only the grouped predictor variables are required. As such, variables should be converted to a numerical interval dummy variable. The levels of the interval variables, or groups are assigned according to distinct levels of risk as defined by the event rate or default rate in this case. This is done per group for each variable under consideration. The bins should produce a monotonic and intuitive event rate curve for a rank ordered variable. The direction of the event rate should make business and statistical sense.

3.6.4 Population Flow

A waterfall of the applications was created to reflect the total number of applications received by the lender over the seven-year period, the exclusions of entries not eligible for the scorecard model development and the final numbers were considered in the analysis. The process entails detailed breakdown of applications approved by the lender as well as the rejects, volumes of loans taken up by SMEs and non-taken up. This study considers applications only up to January 2018 to allow for at least 18 months (February 2018 to July 2019) performance of the loans. Figure 5 shows the population flow of SME loan applications and how the data was prepared for the scorecard model development.

Of the 73,247 approved applications, 44.29 percent were not taken up by the SMEs. This is mainly due to the cold scoring technique used by the lender to grow the business. Cold scoring is a process whereby potential clients are identified using propensity models and other internal processes and their applications are generated by the lender on behalf of the customers. It is the prerogative of the SMEs to take up or decline the offer. The statistics herein show that almost half of the applicants do not take up on this offer probably because they do not need the credit facility offered at the time. On average, about 3.85 percent of SMEs default on loans within the first 18 months of their OD credit facility.

Figure 5: Population Flow



Source: Estimates from research data, 2019

3.6.5 Sample Design

For the application scorecard model development and testing, the study considered all applications received from July 2012 and January 2018 with performance period of 18 months from February 2018 to July 2019. This was segmented into Accepts and Rejects as recorded in Figure 5. Using this segmentation, the data was sampled into the Development data set and Validation data set using a ratio of 80:20 respectively (Marimo & Chimedza, 2017). Table 8 shows the observations allocated in each case.

Table 8: Sample Design

Sample	Category	Observations	Total Observations
Development	Accepts	32647	90922
	Rejects	58275	
Validation	Accepts	8161	22730
	Rejects	14569	

Source: Estimates from research data, 2019

3.6.6 Logistic Regression

The lending criteria in OD is largely depended on customer attributes such as the business sector in which the customer operates, its size, growth stage, affordability and creditworthiness as defined by the scorecard rating. The variables consist of demographics, customer relationships with the bank and external information such as credit bureau data. A performance period was driven by the data for use in the determination of the default event which will be modelled using logistic regression as follows:

$$p(default) = \frac{e^{-\beta_0 + \beta_1 \times Sector + \beta_2 \times Relationship\ with\ bank + \cdots + \beta_n \times Number\ of\ credit\ enquiries}}{1 + e^{-\beta_0 + \beta_1 \times Sector + \beta_2 \times Relationshipwith\ bank + \cdots + \beta_n \times Number\ of\ credit\ enquirie}}$$

The above logistic regression model was fitted with an expectation to produce:

- the main drivers of default
- a probability model to be applied at the point of application
- a tool used to translate into scorecard points, depending on probability levels, that is, the application scorecard.

3.6.7 Reject Inference

To achieve stability and robustness of the estimates, as well as to avoid bias in the scorecard, the application scorecard should consider all applications received by the lender within the outcome period, regardless of whether the application was accepted or rejected. However, the performance information is only available on the accepted and taken-up applications only. If the objective is to measure the impact of the scorecard on all applications, there is need to assign an 'inferred' performance to the rejected applications in the development sample. Reject inference is thus a process whereby the performance of the rejected applications is inferred or estimated. Further, it is important to note that not all approved loans get taken-up. To mitigate this complication, the reject inference is applied in two stages as follows:

1. Assign each reject a probability of taken-up if rendered accepted.
2. Assign each reject a probability of good if estimated to be a Taken-Up (TU).

3.6.8 Goodness of Fit Statistics

The Wald test is a statistical analysis tool used to test that the null hypothesis that all regression coefficients in the model are zero. Significant p-values of values less than 0.05 provide strong evidence, at global level that at least one of the regression coefficients for a predictor variable is different from zero (Kyngäs, H. and Rissanen, 2001). This test will be employed in the study and conclusions related to the significance of the combinations of independent variables will be made.

Various combinations of independent variables will be assessed and compared using goodness of fit measures. The -2 Log Likelihood statistic (-2 LOG L), the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) are some of the commonly used goodness of fit approaches. The AIC and the SBC adjust the -2 LOG L for the number of terms and observations in the model. The SBC considers the number of variables and the size of the sample AIC uses the number of variables only. The SBC is more severe and it favours more parsimonious models. The lower values of AIC or SBC indicate more desirable models.

3.6.9 Gini Statistics

The Gini Statistic (GS) is a measure of strength of a single independent variable against the dependent variable when used in the model as a single input. The GS is also known as Somers' D statistic. It measures uniformity of a distribution and determines its ability to differentiate risk. The less uniformly distributed the variable is, the greater its capability to differentiate risk (Jilek, 2008). Suppose an interval variable with m levels or groups is being assessed for GS in a dataset of N observations, the groups are organized in the increasing order of their event rates. For every group, the number of events is given by n_i^{event} and the non-event by $n_i^{non-event}$. The total number of events = N^{event} and the corresponding non-events = $N^{non-event}$, the GS is determined as follows (Laerd Statistics, 2016):

$$GS = \left(1 - \frac{2 \times \sum_{i=2}^{m}\left(n_i^{event} \times \sum_{j=1}^{i-1} n_j^{non-event}\right) + \sum_{k=1}^{m}(n_k^{event} \times n_k^{non-event})}{N^{event} \times N^{non-event}}\right) \times 100$$

In addition, the variables are checked for population stability over time. For a categorical variable to be useful, there should be a consistent size or volume of entries at each level or group over time. Input or independent variables are expected to make business sense. In addition, the univariate data analysis helps to identify any numerical problems and erroneous data values.

3.6.10 Weight of Evidence

The Weight of Evidence (WoE) is a measure of the strength of each variable in differentiating the bad and good cases and is given by:

$$WoE = ln\left(\frac{g_i}{b_i}\right)$$

Where ln is the natural logarithm of the returned value, g_i represents the proportion of good accounts in group i and b_i represents the proportion of bad accounts in group i of the same variable. The WoE can be positive or negative. Positive WoE implies that the variable isolates a bigger fraction of good cases than bads and the converse is true for negative WoE. The larger the difference of the WoE between groups, the higher the predictive power of the variable. In addition, it is expected to have a monotonic trend in the WoE of predictor variable before the variable can be included in the model. The use of WoE transformation as input values for the model development offers a way to deal with differing input units (numeric and categorical).

Independent variables passing the univariate process are considered jointly in selecting a candidate model through stepwise regression analysis. The results usually complement the correlation analysis where one on one correlation coefficient of predictor variables is computed. Whilst several variations exist, the multivariate selection process to be used in this study is the stepwise regression. The study made use of the forward selection criteria. The process starts with an empty model, computes a chi-square statistic for each covariate not in the model and selects the one with the largest value. If the covariate meets the significance criteria, then it is added to the model. The process is repeated until none of the remaining variables meets the specified level of entry (Melfi, 2004). The reason why forward selection is preferred over other selection techniques such as backward selection has to do with the fact that the baseline of the logistic regression model diminishes with every added variable. A baseline with low volume will introduce larger error into the model which may impact the accuracy of the statistics calculated for variable inclusion. Thus, it is preferred to start with no variables and a well-populated baseline when fitting the logistic regression model.

3.6.11 ROC Curve

The Receiver Operating Characteristic (ROC) curve or Lorenz curve plots sensitivity against 1-specificity of each of the models to be compared. The plot is run at different cutoff values of risk. Given the target variable (whether the applicant defaulted on the loan or not) “Sensitivity is a fraction of accounts in default that the model correctly identifies as defaulted. Specificity refers to a fraction of accounts not in default that the model correctly identifies as not in default", (Marimo & Chimedza, 2017). The horizontal axis represents 1- specificity while sensitivity is plotted on the vertical axis. The diagonal line on the plot represent a random or useless model. A good model with the ability to differentiate risk lies at the uppermost left part of the ROC cartesian plane. The Area Under the ROC Curves (AUC) also explains the ability of the models to separate the good and bad cases. The higher the AUC value, the better the model. ROC approach was used herein to compare models including and excluding the bureau information. The chosen model was then used to assign scorecard points to each variable in the final model.

3.7 Summary

This Chapter highlighted the data sources, the sampling design and the methodologies to be followed in this investigation. The relationship between demand/supply of SME credit and economic growth is of key importance. The technical details of developing an application scorecard entails historic data extraction, exploratory data analysis, data cleaning, univariate and multivariate data analyses. SME application for overdraft facility data are provided over a seven-year period from July 2012 to July 2019. Outcome period analysis offers sufficient workout observation on all applications and helps remove biasness in the model. The analytical framework and theoretical view on the use of a binary target logistic regression methodology was discussed in this Chapter. Goodness of fit statistics are global model diagnostic tests evaluating the validity of the models and can be used to compare models.

CHAPTER 4: DISCUSSION OF FINDINGS

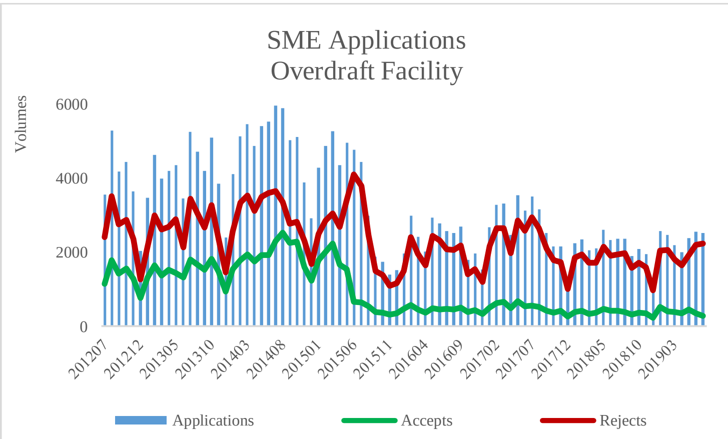
4.1 Introduction

This chapter details the in-depth analysis of the SME credit patterns and the development of an application scorecard using the credit scoring methodology developed by Siddiqi (Siddiqi, 2006). The analysis is set out to reflect the SME credit industry in accordance with trends in the domestic, economic, financial and legislative environment. The statistical analysis was conducted in SAS® Enterprise Guide, summarised in Microsoft (MS) Excel and reported in MS Word.

4.2 Exploratory Data Analysis

This section describes the structure of the available data. From 278,886 applications received over the seven-year period, July 2012 to July 2019, the lender declined a substantial 198,678 applications, making up 71.2% of the total. The term "rejects" refers to the subpopulation of loan applications the lender declines due to various reasons. These include failure to meet the acceptance cut-off score by the existing scorecard, failure to comply with credit policy rules under the NCA or manual overrides driven by acquisitions criteria and the lender's risk appetite. It can be observed from Figure 6 that the volumes of applications (demand) received per month significantly plummeted from an average of 4000 prior to 201507 to 2000 in the latest period. The number of rejects is consistently higher than the accepted applications (supply). The application process is seasonal or cyclical as the volumes sizeably drop in January each year. The patterns reflecting the demand and supply of SME credit may be driven by changes in the economy. An investigation was conducted using the available the macroeconomic indicators and the analysis is detailed in Section 4.3

Figure 6: SME Applications over Time



Source: Research Data, 2019

Table 9: Summary Statistics for SME Loan Applications

Variable	Mean	Std Dev	Minimum	Maximum
Total Number of Applications	3273	1271	1205	5958
Accepts (rate)	943 (29%)	658	233	2530
Rejects (rate)	2330 (71%)	715	972	4099

Source: Estimates from Research Data, 2019

The summary statistics of the volume of applications, accepts and rejects observed over a period 85 months are provided in Table 9. The maximum number of applications were received in July 2014. In the same month, the highest number of accepts were observed. The least figures in both instances were observed in December 2018. It is interesting to investigate how these trends complement activities in the economy and the financial environment through the movements in macroeconomic factors and macroprudential indicators.

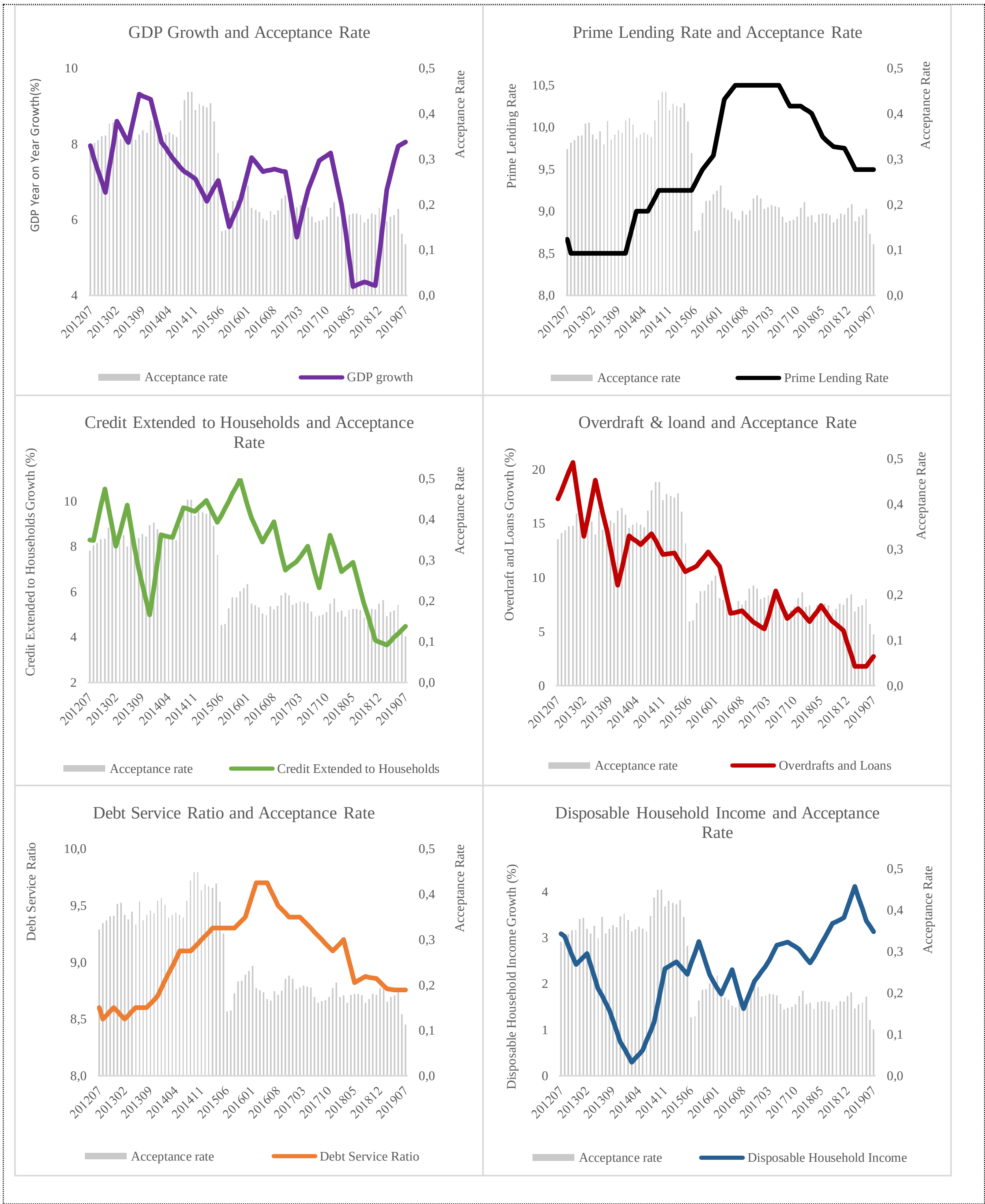
4.3 Time Series Analysis

For each month in observation, the acceptance rate (supply) is the total number of accepts divided by the total number of applications received for the month. The macroeconomic factors as well as the macroprudential indicators were sourced from Moody's rating agency. Variables listed in Table 4 were considered relevant to the risk inherent in SME credit industry and were assessed as potential economic drivers of SME credit patterns.

The time series plot of the acceptance rate and each of these variables is shown in Figure 7. The acceptance rate follows similar trend to Overdraft and Loans (OL). The year on year OL rate has declined drastically overtime reflecting the worsening credit extension in the financial industry. The drop in the acceptance rate during the last quarter of 2015 aligns to an increase in the prime lending rate which translated into high borrowing costs, making it difficult for the firms to submit applications for commercial bank funding and for lenders to extend loans. The acceptance rate pattern is intuitive to the movements in PLR.

For these potential drivers, a sensibility test was devised to assess whether the correlations of these indicators are in line with logical expectations. For example, it is expected that the acceptance rate would increase as the GDP increases, giving a positive correlation between the acceptance rate and GDP. The sensibility test results are provided in Table 10.

Figure 7: Time Series of Macroeconomic Factors and Macroprudential Indicators



Notes: GDP= Gross Domestic Product; Prime=Prime Lending Rate; DSR = Debt Service Ratio; DHI Disposable household Income; OL= Overdrafts and Loans; CEH = Credit Extended to Households; AR = Acceptance Rate

Source: Estimates from research data, 2019

Table 10: Sensibility Test - Macroeconomic Indicators

Macroeconomic Indicator	Correlation Coefficient	Sensibility Test	Gini Statistics (Variable Importance)
GDP	+45.84%	Pass	23.36
Prime	-74.81%	Pass	36.16
DSR	-34.92	Fail	N/A
OL	+75.65%	Pass	47.62
DHI	-55.61%	Fail	N/A
CEH	+43.65	Pass	33.17

Source: Estimates from research data, 2019

4.3.1 Unit Root Tests

The time series diagnostics delved into intricacies of stationarity and cointegration embedded in macroeconomic variables and macroprudential indicators ahead of the regression analysis. Unit root tests were performed using the ADF procedure on intercepts and trends of individual variables. The null hypothesis indicates the presence of unit root. Using the SBC criteria, the analysis was performed on the level and first lag length (lag = 1) for all series. Based on the results provided in Table 11, we fail to reject the null hypothesis of the presence of a unit root in levels for Prime and CEH and conclude that both variables are integrated of the first order. We reject the existence of unit root null hypothesis in both variables when the first difference is considered. This implies that the two variable exhibit stationarity only on first difference. The unit root hypothesis is rejected for GDP and OL in both level and first differential implying that the two series exhibit stationarity. As shown in Table 11, all the series are stationary at first difference. Thus, for cointegration purposes, it was decided to use the Johansen test. This was done separately for the demand and supply variations of the study. The results are provided in the ensuing sections.

Table 11: Unit Root Test

	Unit Root Tests			
	Level		First Difference	
	Fisher ADF	P-value	Fisher ADF	P-value
GDP	7.380	0.027	9.730	0.001
OL	14.120	0.001	19.620	0.001
PLR	2.490	0.682	7.280	0.029
CEH	5.270	0.139	18.200	0.001
AR	2.337	0.021	6.995	0.004
Volume	3.447	0.038	17.729	0.000

Source: Estimates from research data, 2019

4.3.2 Determinants of Demand for Credit

Table 12: Cointegration Test: Demand for Credit

Hypothesis Test of the Restriction					
Rank	Eigenvalue	Restricted Eigenvalue	DF	Chi-Square	Pr > ChiSq
0	0.2449	0.2450	5	3.40	0.6380
1	0.2080	0.2147	4	3.39	0.4952
2	0.1332	0.1398	3	2.68	0.4443
3	0.1035	0.1244	2	2.04	0.3614
4	0.0641	0.0649	1	0.08	0.7838

Source: Estimates from research data, 2019

The Johansen Cointegration test indicates no cointegration at the 5% level, therefore the Vector Autoregression (VAR) model was performed and the results are provided in Table 13. Model diagnostics metrics are satisfactory with an R^2 of 71.46% and a significant global F-test.

Table 13: Demand for Credit VAR Model

Volume - Model Parameter Estimates				
Parameter	Estimate	Std. Error	t-Value	Pr > |t|
CONSTANT	3.32694	2.52804	1.32	0.1923
$Volume_{(t-1)}$	0.63973***	0.11437	5.59	0.0001
GDP_{t-1}	0.06859	0.55176	0.12	0.9014
OL_{t-1}	-0.08421	0.05174	-1.63	0.1080
CEH_{t-1}	1.16715*	0.66481	1.76	0.0834
PLR_{t-1}	1.34007	4.50970	0.30	0.7672
$Volume_{t-2}$	0.01264	0.11575	0.11	0.9133
GDP_{t-2}	0.01298	0.55358	0.02	0.9814
OL_{t-2}	0.09444*	0.05427	1.74	0.0861
CEH_{t-2}	-1.19658*	0.68489	-1.75	0.0849
PLR_{t-2}	-1.67639	4.32279	-0.39	0.6993
R-Square	0.7146			
F-test	18.03			
Pr > |F|	<.0001			

Source: Estimates from research data, 2019

*Note: ***, **, and * denote that the parameter estimate is significant at the 1%, 5% and 10% levels respectively.*

Results from the VAR analysis show that, the volume of loan applications and CEH at their first lags as well as OL and CEH at the second lags are the main determinants of demand for credit. The positive value in estimates indicate that the higher the factor, the higher the demand for credit at the point of observation. The converse applies for the negative estimates such as the second lag in CEH.

4.3.3 Determinants of Credit Supply

Table 14: Cointegration Test: Credit Supply

Hypothesis Test of the Restriction					
Rank	Eigenvalue	Restricted Eigenvalue	DF	Chi-Square	Pr > ChiSq
0	0.2384	0.2397	5	3.63	0.6040
1	0.1711	0.1770	4	3.48	0.4804
2	0.1468	0.1532	3	2.89	0.4085
3	0.0845	0.1040	2	2.27	0.3220
4	0.0616	0.0669	1	0.47	0.4908

Source: Estimates from research data, 2019

The Johansen Cointegration test indicates no cointegration at the 5% level, therefore, the VAR model was performed, and the results are provided in Table 15. Model diagnostics metrics are satisfactory with an R^2 of 93.47% and a significant global F-test at 5% level of significance.

Table 15: Credit Supply VAR Model

Acceptance Rate - Model Parameter Estimates				
Variable	Estimate	Std. Error	tValue	Pr > |t|
CONSTANT	0.05378	0.80321	0.07	0.9468
AR_{t-1}	1.03392***	0.11399	9.07	0.0001
GDP_{t-1}	-0.34369	0.26935	-1.28	0.2061
OL_{t-1}	-0.05110	0.18027	-0.28	0.7776
CEH_{t-1}	0.26911	0.25192	1.07	0.2890
PLR_{t-1}	-0.07142	2.09168	-0.03	0.9729
AR_{t-2}	-0.24689**	0.11552	-2.14	0.0360
GDP_{t-2}	0.36090	0.27128	1.33	0.1876
OL_{t-2}	0.19490	0.17556	1.11	0.2706
CEH_{t-2}	-0.38657	0.25879	-1.49	0.1396
PLR_{t-2}	-0.13788	2.11101	-0.07	0.9481
R-Square	0.9347			
F-test	103.13			
Pr > |F|	<.0001			

Source: Estimates from research data, 2019

*Note: ***, **, and * denote that the parameter estimate is significant at the 1%, 5% and 10% levels respectively.*

The major determinants driving the acceptance rate of SME loan applications are the acceptance rate at first and second lags of the time series. It is highly likely for the loans to be approved if the acceptance rate was higher in the previous month and the converse is true for the two-month lag. It is important to note the recursive parameterization shortcoming of the VAR methodology (Onoja et al., 2017) as the prediction can be estimated from the same variable as is the case in the prediction of the acceptance rate. The additional multiple interdependencies of variables are provided in Appendix B.

4.4 Application Scorecard Model Development

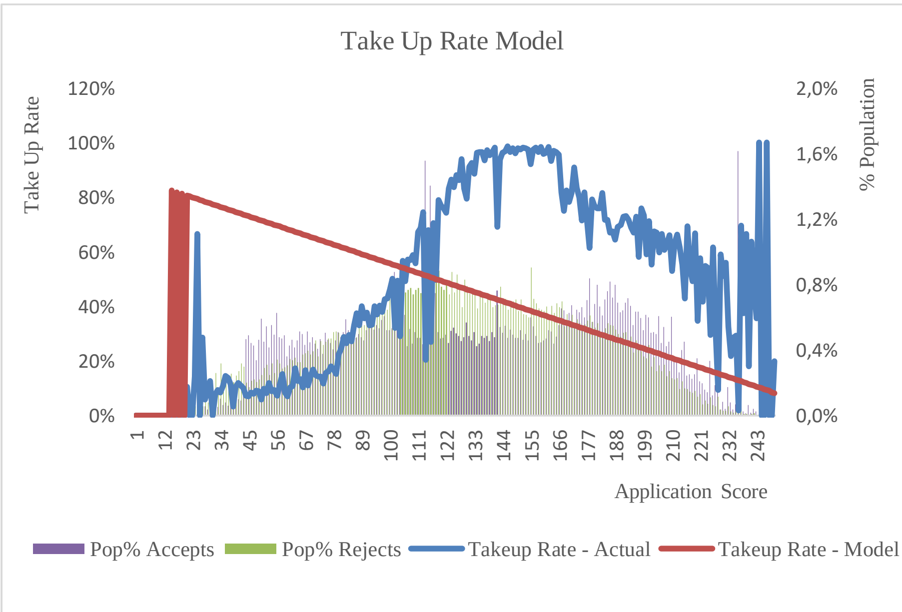
The application scorecard can be used to decide whether to extend credit to applicants with an aim to reduce defaults and serious delinquencies on new applicants. In addition, the model can also be used to allocate capital, determine risk tendency and monitor the performance of the portfolio in scope. Risk characteristics under Basel Accords should be calculated and used in conjunction with the scorecard for risk management purposes (BCBS, 2017).

4.4.1 Reject Inference

➢ *Stage 1: Infer Non-Taken Up Applications*

The first stage in reject inference is to assign the Non-Taken-Up (NTU) records within the rejected population. All the accepted applications from the development sample were used to infer the TU and NTU probabilities to the rejected records. The application score of the principal business owner was used as a proxy for the credit performance of each SME across its loans. This score was used to fit a relationship between TU and NTU applications. As shown in Figure 8, an inverse relationship is observed between the application score and the TU rate where a higher score results in a lower TU rate.

Figure 8: Take Up Rate Model



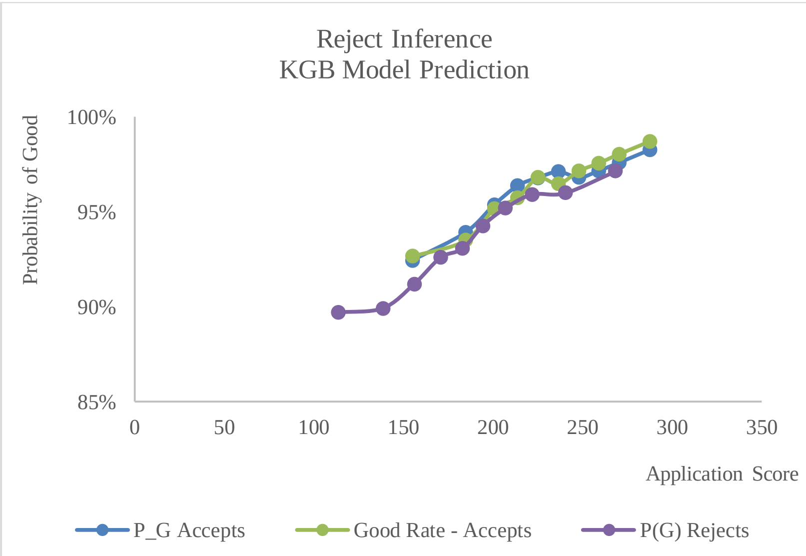
Source: Estimates from research data, 2019

This relationship is intuitive because if offered a loan, the worse performing applicants (lower score) are likely to take up on the offer compared to the low risk (high score) applicants.

- *Stage 2: Infer Reject Good and Bad Applications*

The second stage in reject inference is to assign the probability of good to rejects if estimated to have taken up the loan. This is based on the Known Good Bad (KGB) model built on the subpopulation with known performance (accepted and taken up). The model is based on fitting the application score at outcome point to obtain a relationship between good and bad accounts. The purpose is to predict the probability of TU account being good or bad at outcome. Logistic regression was applied to develop the KGB model. Figure 9 shows the prediction of the KGB model on rejects and accepts. The trend is intuitive as the probability of good is consistently lower for the reject population. With the reject inference completed, the application scorecard can be developed on a full spectrum of applications received by the lender.

Figure 9: KGB Model Prediction



Source: Estimates from research data, 2019

4.4.2 Reject Inference Validity

In application scorecard development, the Good: Bad odds ratio for accepts and inferred rejects usually falls in the range of 2 to 6. The known to inferred ratio of 2.03 given in Table 16 is an indication that the reject inference results are satisfactory.

Table 16: Ratio of Known Odds to Inferred Odds

Sample		Number of Observations	Badrate	Odds Ratio
Accepts	Goods	31389	3.85%	24.95151033
	Bads	1258		
	Total	32647		
Rejects	Goods	53889	7.53%	12.28662295
	Bads	4386		
	Total	58275		
Development (Accepts + Rejects)	Goods	85278	6.21%	15.10952864
	Bads	5644		
	Total	90922		
Known to Inferred Odds Ratio			2.03078669	

Source: Estimates from research data, 2019

4.4.3 Univariate Analysis

The initial list of variables available for scorecard development consisted of all the information captured during the loan application process. A multitude of over a hundred fields was reduced by removing variables based on the following criteria: variables with only one attribute across applicants, variables which are not sufficiently or correctly populated, variables not applicable for the scorecard and variables that are represented by other characteristics. An ensuing list of fifteen variables or characteristics eligible for consideration in the model development was then selected based on the expert judgement and general logic of the author. Each characteristic was grouped and transformed into its WoE.

A preliminary step performed before estimating the scoring model was to conduct a univariate analysis for each variable. The purpose was to identify variables which make sense in a business context, can be surveyed with relative ease and which show high discriminatory power for the purpose of developing the scoring function. Univariate analysis helps reduce the complexity of the ensuing multivariate analysis, thus facilitating the model development process substantially. Through a series of statistical analyses, individual variables in Table 7 were each examined for eligibility in the final scorecard development.

Univariate analysis alone served to reduce the catalogue of fifteen variables down to eight, as shown in Table 17 for consideration in the multivariate analysis stage of the model build process. The Population Stability Index (PSI) measures the stability of population in each group of a classed variable. A stable PSI has a value of 0.1 or less (Marimo & Chimedza, 2017). With reference to Section 3.6.6, an individual variable is deemed to be able to differentiate risk if its GS compared to the dependant variable is at least 4. Further, the WoE across the groups of an individual variable need to be monotonic and the volume of observations in each group should be at least five percent. Figure 13 in Appendix B provides the WoE and population of observations in each variable. The variables violating the preceding conditions were excluded from the analysis. Variable selection criteria is summarised in Table 17.

Table 17: Univariate Statistics

	Variable	Source	Gini Statistics	PSI	Inc.	Reason For Exclusion
1	Excess	Internal	17.16	0.0323	Yes	N/A
2	Credit Enquiries	Bureau	21.80	0.0203	Yes	N/A
3	Time since Last Transaction	Internal	11.67	0.0326	Yes	N/A
4	Time with Lender	Internal	24.28	0.0593	Yes	N/A
5	Sector	Internal	9.53	0.0022	Yes	N/A
6	Worst Excess	Bureau	8.99	0.5041	Yes	Unstable
7	Worst Bureau Report	Bureau	9.93	0.0068	Yes	N/A
8	Enquiries Recent	Bureau	16.12	0.4157	Yes	Unstable
9	Time since payment profile	Internal	13.34	0.9400	No	Unstable
10	Time since last enquiry	Bureau	18.06	0.5490	No	Inability to differentiate risk
11	Worst Report Recent	Bureau	6.82	0.5510	No	Inability to differentiate risk
12	Worst Ever Arrears	Bureau	19.35	0.9810	No	Unstable
13	Time since last transaction	Internal	16.25	0.5670	No	Unstable
14	Cheque Account Transaction	Internal	2.11	0.7220	No	Inability to differentiate risk
15	Guinness Rating	Internal	19.77	0.6820	No	Unstable

Source: Estimates from research data, 2019

4.4.4 Multivariate Analysis

Multivariate analysis entails statistical procedures used to determine how the independent variables considered for further analysis work together in the model fitting process. Multicollinearity diagnostics were used to select the characteristics for the initial models. Stepwise Logistic Regression as discussed in Section 3.6.6 was used to fit subsequent models after multi-collinearity has been removed. Models were examined for logical trend, for example, reverse signs on parameter estimates whilst aiming for parsimonious models, i.e. minimisation of the number of variables whilst not losing predictive power. Validation of model fit on the independent hold out (validation) sample was performed. The resultant models including and excluding bureau information were compared using various statistical measures.

4.4.5 Model Fitting: Internal and Bureau Variables

Table 18: Model 1 - Internal and Bureau Variables

Model 1 - Internal and Bureau Variables						
Parameter	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Odds Ratio**	**Z-Statistics**	**P-Value**
Intercept	2.7155	0.0146	34676.980	15.112	186.2176	<.0001
Excess	-0.5027	0.0438	131.8428	1.653	11.48228	<.0001
Credit Enquiries	-0.9213	0.0377	596.2210	2.513	24.41764	<.0001
Time since Last Transaction	-0.7320	0.0583	157.54960	2.079	12.55188	<.0001
Time with Lender	-0.6970	0.0310	505.7309	2.008	22.48846	<.0001
Sector	-0.7426	0.0521	202.7845	2.101	14.24024	<.0001
Worst Bureau Report	-0.6899	0.0497	192.3296	1.994	13.86829	<.0001
Likelihood Ratio			2611.2488			<.0001
Score			2650.6101			<.0001
Wald			2495.5706			<.0001
N	**90922**					

Source: Estimates from research data, 2019

Parameter estimates of the six variables are all significant at 95% confidence level. The global tests show that the model with covariates is significantly different from a null model. Variables selected are significant drivers of the default rate in the SME credit industry.

4.4.6 Model Fitting: Internal Variables Only

Table 19: Model 2 - Internal Variables Only

Model 2 - Internal Variables Only						
Parameter	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Odds Ratio**	**Z-Statistics**	**P-Value**
Intercept	2.717	0.0144	35810.95	15.135	189.2378	<.0001
Excess	-0.5425	0.0434	156.2004	1.720	12.49802	<.0001
Time since Last Transaction	-0.6847	0.0579	140.0839	1.983	11.8357	<.0001
Time with Lender	-0.8261	0.0305	735.7736	2.284	27.12515	<.0001
Sector	-0.8053	0.0518	241.2156	2.237	15.53112	<.0001
Likelihood Ratio			1856.5968			<.0001
Score			1864.4482			<.0001
Wald			1786.9986			<.0001
N	**90922**					

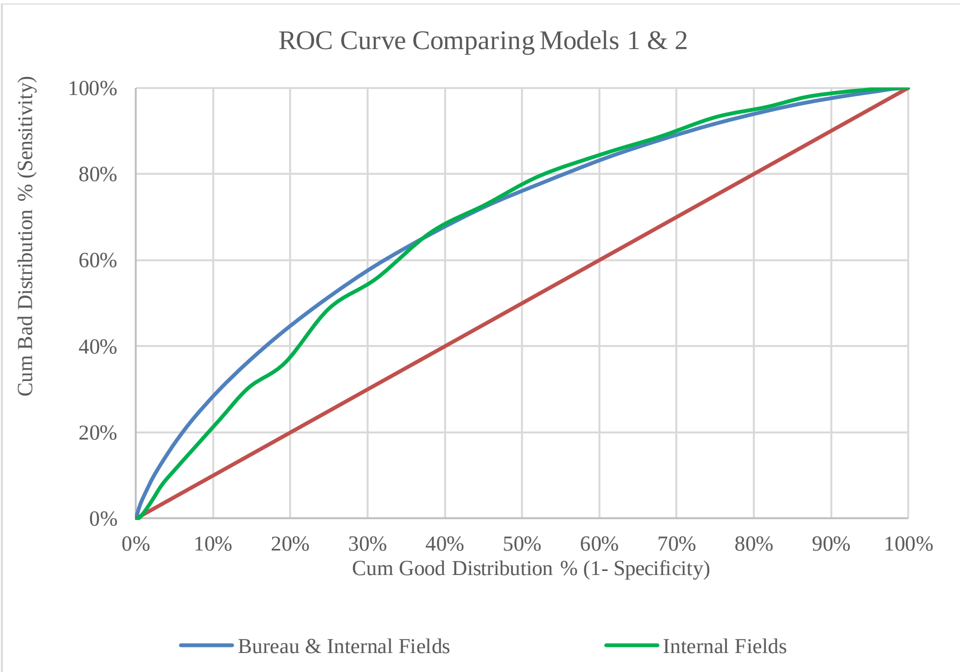
Source: Estimates from research data, 2019

The model built on internal variables only is significant both at global level and at individual parameters. Thus, the model is significantly different from a null model. Model 1 and Model 2 were compared to determine the benefit of inclusion/exclusion of bureau information in the SME Application Scorecard.

4.4.7 Final Model Selection

The two models described in the preceding sections were compared using various statistical measures. Both models were applied to the validation sample to ascertain model fitness. Satisfactory results were observed in both cases. In hindsight, the benefit of including/excluding rejected applications in the models was determined.

Figure 10: ROC Curves



Source: Estimates from research data, 2019

Table 20: Final Model Selection Criteria

AUC	Development Sample		Validation Sample		% Increase in AUC (Development)	% Increase in AUC (Validation)
By Scorecard	Accepts & Rejects	Accepts Only	Accepts & Rejects	Accepts Only		
Bureau & Internal Fields (Model 1)	38.4	37.6	38.6	37.5	2.07%	2.96%
Internal Fields Only (Model 2)	32.6	30.8	32.3	29.7	5.76%	8.69%
% increase in Gini	18.0%	22.2%	19.3%	25.9%		

Source: Estimates from research data, 2019

Table 20 provides measures of the discriminatory power of the models. An eighteen percent increase in GS is realised when the Bureau information is added as part of the covariates. A benefit of 2.07 percent in discriminatory power is realised if the scorecard model development includes the reject inference process. Similar trends were observed in the validation sample. Further, this is confirmed by the ROC curve (Lorenz curve) in Figure 10 that Model 1 exhibits a better discriminatory power than Model 2 as it lies closer to the top left quadrant of the plot.

4.4.8 Scorecard Points

Model 1 (Internal + Bureau Fields) was finally selected as the best model for application in the development of the SME scorecard. The model was fitted to the development set to obtain probabilities of default. These probabilities were then converted into scorecard points per variable per category within each variable. Scorecard points are linked to the probabilities returned by the model in each case. The intuitiveness of scorecard points, badrate and WoE for every variable in scope is provided below.

4.4.9 Final Variable Statistics

1. *Credit Enquiries*

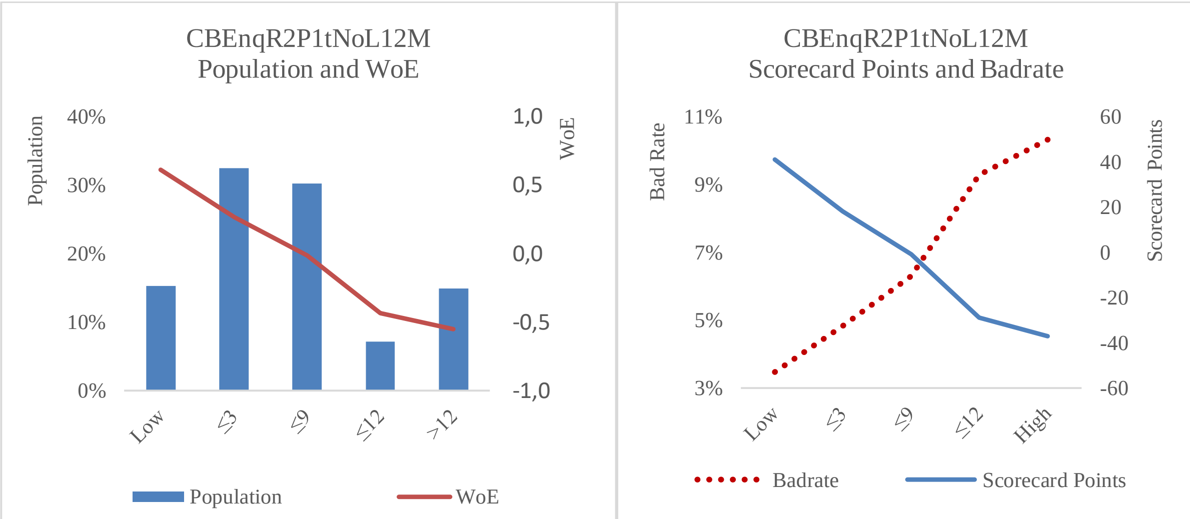
Table 21: Credit Enquiries

Credit Enquiries	Scorecard Points	WoE	Goods	Bads	Badrate
01 : Low to <= 1	41	0.6118	13365.72404	479.7830401	3.47%
02 : > 1 to <= 3	18	0.2644	28089.19044	1427.123515	4.84%
05 : > 3 to <= 9	-1	-0.0162	25733.06009	1730.913592	6.30%
11 : > 9 to <= 12	-29	-0.4354	5921.000083	605.6545366	9.28%
12 : > 12 to High	-37	-0.5533	12168.92992	1400.507112	10.32%

Source: Estimates from research data, 2019

The variable Credit Enquiries is a bureau field detailing the number of enquiries made by the applicant in the past twelve months. It satisfied the univariate analysis criteria as shown in Figure 11. The population in each group exceeded five percent. The bad rate, WoE and the scorecard points curves are intuitive and monotonic. The larger the number of enquiries, the more uncertain and riskier the applicant is. The bad rate increases with an increase in the number of enquiries. Risky applicants have been allocated the lowest scorecard points. This analysis was conducted for each of the final six variables and the results were satisfactory.

Figure 11: Univariate Selection Criteria



Source: Estimates from research data, 2019

2. Time since Last Transaction

Table 22: Time since Last Transaction

Time since Last Transaction (months)	Scorecard Points	WoE	Goods	Bads	Badrate
0	16	0.2957	14383.31677	708.2523992	4.69%
00: Missing	-3	-0.0543	13879.35187	969.8282712	6.53%
03 : > 0 to <= 5	7	0.136	38048.75622	2198.078426	5.46%
08 : > 5 to <= 10	-12	-0.2207	8968.773373	740.1437171	7.62%
10 : > 10 to <= 25	-20	-0.3771	7150.569308	690.0311119	8.80%
13 : > 25 to High	-31	-0.5833	2847.13702	337.6478697	10.60%

Source: Estimates from research data, 2019

The higher the number of months since an applicant's last credit transaction, the greater the likelihood of the applicant not having enough funds to meet debt obligations and thus the higher the risk of default. Thus, the worst scorecard points allocation falls in the highest bracket of this variable.

3. Time with Lender

Table 23: Time with Lender

Time with Lender (months)	Scorecard Points	WoE	Goods	Bads	Badrate
1:00 New to Bank	6	0.117	11255.50475	662.6782406	5.56%
02 : > 0 to <= 12	-48	-0.9461	4417.26264	753.01663	14.56%
03 : > 12 to <= 18	-35	-0.6935	3383.392057	447.9991329	11.69%
04 : > 18 to <= 24	-25	-0.5003	3025.404126	330.2269838	9.84%

05 : > 24 to <= 33	-20	-0.4016	3836.680936	379.4216338	9.00%
06 : > 33 to <= 54	-10	-0.1891	7740.215539	618.9333206	7.40%
08 : > 54 to <= 63	-6	-0.1149	3114.742058	231.2523917	6.91%
09 : > 63 to <= 75	3	0.0687	4366.76174	269.8152901	5.82%
10 : > 75 to <= 84	8	0.1635	3381.998157	190.0766928	5.32%
11 : > 84 to <= 93	11	0.2145	3332.768537	177.9909928	5.07%
12 : > 93 to <= 138	14	0.2876	15351.55696	762.0391878	4.73%
16 : > 138 to <= 153	17	0.3315	4098.585437	194.7132633	4.54%
17 : > 153 to <= 270	29	0.5847	14499.19024	534.7366452	3.56%
21 : > 270 to High	47	0.9259	3473.841391	91.08138948	2.55%

Source: Estimates from research data, 2019

Applicants who have been the lender's clients for a longer time period are perceived to have a low default risk and have therefore been allocated with the highest scorecard points.

4. *Excess*

Table 24: Excess

Excess	Scorecard Points	WoE	Goods	Bads	Badrate
01: High	-18	-0.4858	5946.34370	639.720802	9.71%
06: Medium	-9	-0.2454	39080.1601	3305.75989	7.80%
03: Low	16	0.4439	37921.0940	1610.06386	4.07%
05: Never	20	0.5561	2330.30662	88.43723469	3.66%

Source: Estimates from research data, 2019

At the point of application, customers are allocated excess levels. Business entities which have never been in excess are perceived to have a low default risk and have been awarded the highest scorecard points.

5. *Sector*

Table 25: Sector

Sector	Scorecard Points	WoE	Goods	Bads	Badrate
01 : Missing	113	2.1039	5.765305757	0.046544243	0.80%
02: Retail	6	0.1142	39248.31299	2317.178511	5.57%
03: Construction	-17	-0.3248	19488.07644	1784.704503	8.39%
04: Transport	-14	-0.2592	5922.884616	507.9624441	7.90%
05: Trade	-5	-0.0922	5562.503692	403.698418	6.77%
06: Services	56	1.0488	3535.99568	81.99309005	2.27%
07: Manufacturing	18	0.329	11514.36585	548.3982848	4.55%

Source: Estimates from research data, 2019

Of the non-missing categories, the services sector has been observed to be the best performing with the least bad rate. Construction industry has been the riskiest and therefore allocated comparatively the lowest scorecard points.

6. *Worst Bureau Report*

Table 26: Worst Bureau Report

WrstCBReport	Scorecard Points	WoE	Goods	Bads	Badrate
01: C (Worst)	-51	-1.0295	31.84074861	5.899801386	15.63%
02: D	-3	-0.0694	3976.712801	282.1089394	6.62%
03: F	36	0.7191	727.4598513	23.45613871	3.12%
04: N	6	0.1158	66224.36464	3903.819676	5.57%
05: O	-27	-0.5364	8032.360169	909.009951	10.17%
06: S	-19	-0.373	5232.890076	502.9072244	8.77%
07: X (Best)	71	1.4232	1052.276276	16.78006413	1.57%

Source: Estimates from research data, 2019

The worse the principal's credit bureau report, the higher the risk of default and thus, the lower the scorecard points allocated.

4.4.10 Scoring Alignment Parameters

The scorecard is aligned to:

- A score of 500 has Good: Bad odds of 5:1
- 50 points double the odds

These parameters were chosen in order to reflect the portfolio bad rate at the reference score. In this case, the development sample odds ratio is 15.11 as shown in Table 27. For a score of 500 to represent this and a bad rate of 6.21%, the following function is used to determine the Reference Odds (RO):

$$Reference\ Odds = \frac{1}{Odds\ Ratio_{Development}} - 1 = \frac{1}{0.1511} - 1 \approx 5$$

Figure 12 and Table 28 demonstrate the relationship between the theoretical Odds, Log (Odds) and bad rate for these alignment parameters.

Table 27: Scorecard Alignment Parameters

Alignment Parameter	Value
Bad Rate (Accepts + Rejects)	6.21%
Reference odds	15
Reference Score	500
Points to double odds	50

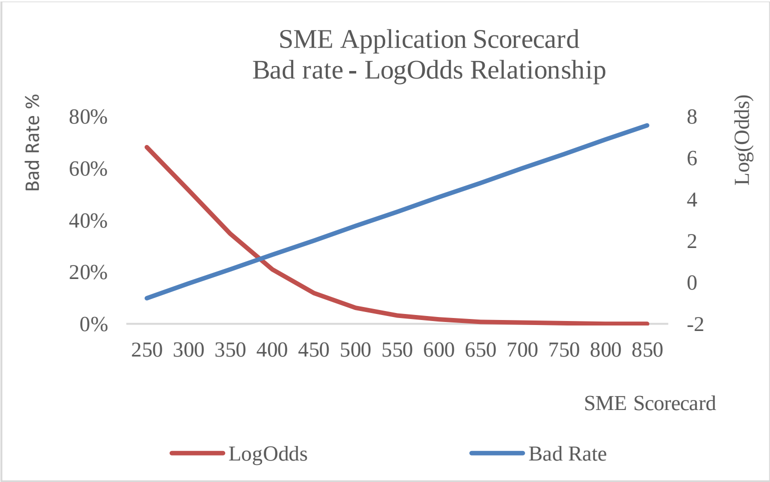
Source: Estimates from research data, 2019

Table 28: The SME Application Scorecard

Scaling: 500 = 5:1 with 50 points to double the odds					
Score	**Goods (G)**	**Bads (B)**	**Odds (G/B)**	**Log(Odds)**	**Bad Rate (B/G+B)**
250	0.5	1	0.46875	-0.758	68.09%
300	0.9	1	0.9375	-0.065	51.61%
350	1.9	1	1.875	0.629	34.78%
400	3.8	1	3.75	1.322	21.05%
450	7.5	1	7.5	2.015	11.76%
500	15.0	1	15	2.708	6.21%
550	30.0	1	30	3.401	3.23%
600	60.0	1	60	4.094	1.64%
650	120.0	1	120	4.787	0.83%
700	240.0	1	240	5.481	0.41%
750	480.0	1	480	6.174	0.21%
800	960.0	1	960	6.867	0.10%
850	1920.0	1	1920	7.560	0.05%

Source: Estimates from research data, 2019

Figure 12: Bad Rate - Log (Odds) Relationship



Source: Estimates from research data, 2019

4.4.11 SME Scorecard Implementation

At the point of loan application, the client profile gets scored according to the respective scorecard points allocation of the six variables above. A constant of 500 discussed in the preceding section gets added to the total score of applicants obtained from each of the six drivers of risk. Table 27 shows the alignment parameters linking the total score of individual applications to the scorecard. The scorecard rejects any applications with scores less than 500 and accepts applications scoring 500 points or more.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter concludes the study on survival of the fittest SMEs in accessing commercial bank funding in South Africa. This entails a summary of the investigation and the conclusions drawn from the empirical research findings. Further, this chapter highlights the limitations of the underlying investigation and lastly provide recommendations to various stakeholders in the SME credit industry to improve the current state of credit supply and ideas for future research.

5.2 Summary of the Study

To examine the credit quality of SMEs and to investigate the linkage between the domestic economy and the SME credit industry, this study made use of a wealth of information extracted from one of the leading banks in South Africa. Based on the applications submitted for the overdraft facility, monthly application cohorts were drawn over a period of seven years from July 2012 to July 2019. The information comprised a multitude of variables or fields populated against thousands of applications received by the lender for every month in observation. Variables spanned the entire spectrum of dimensions, from standard fields such as unique application number and month of application to risk related attributes such as the industry in which the SME operate and its relationship with the bank. To enhance stability and relevance of the outcomes, external data were sourced from Moody's and Experian. Macroeconomic factors and macroprudential indicators were obtained from Moody's, a top global credit rating agency whilst credit data for the individual principal business owners were sourced from Experian, one of the renowned credit bureau institutions in South Africa.

Exploratory data analysis revealed a significant decline in the number of applications received over time during the period under investigation. Subsequently, the success rate in obtaining loans as reflected in the acceptance rate plummeted drastically in 2015 at a point when the prime lending rate increased. This intuitively translated into an increase in borrowing costs and therefore notable scepticism on the part of borrowers to submit applications and the lender to issue loans. Multiple correlation analyses and econometrics approaches were employed to determine the statistical relationship between changes in the economy as reflected by the macroeconomic factors and macroprudential indicators and the success rate of accessibility to funding as well as the demand for credit within the SME sector. The analysis showed a highly positive relationship between economic growth and accessibility to bank loans.

The known application scorecards for SMEs were developed and implemented in developed countries such as the US and UK. In these countries, the use of pooled data (where data comes from multiple lenders) in formulating SME scorecards proved to be a success in terms of cost effectiveness, improved bad debt management and regulatory compliance on the back of enhanced risk control in the developed world. This has not effectively been developed for and implemented in developing countries due to data scarcity and the bureaucratic nature of the businesses. It was worthwhile therefore to develop an application scorecard bespoke to SMEs for one of the leading banks under the presumption that this can be generalised for the countrywide SME credit industry. Drawing on learnings from the developed world, this study adopted a similar approach by developing an application scorecard bespoke to SMEs in an emerging market context but from a single money lending financial institution. The application scorecard developed in this study is set to enable the lenders to quantify the risk associated with SME loan applicants and offer improvements on objective decision-making processes and reduces transaction costs as seen in the developed world as highlighted in literature.

A sophisticated binary target logistic regression statistical approach was used in the development of the SME application scorecard. The target or dependent variable was derived as an indicator of whether the borrower defaulted on its overdraft facility within the first eighteen months of access to the loan. Independent or explanatory variables were assessed so that insufficiently or incorrectly populated fields were excluded from the analysis. Fields concentrated with one attribute were also removed. The final list was selected based on the expert judgement of the author as well as statistical selection criteria such as monotonicity of the bad rate, monotonicity of weight of evidence, population stability on coarse classification of the variable over time and its ability to differentiate risk through Gini Statistics. Selection guidelines for each of the approaches were precisely followed. Univariate analysis reduced a catalogue of more than a hundred potential explanatory variables down to fifteen. In a multivariate analysis context, explanatory variables were assessed for multicollinearity and this further reduced the final list of variables to six, two of which were obtained from the bureaux.

Given that the application scorecard is developed for use on through the door applicants, it was imperative to design a model that reflects the riskiness of SME borrowers. Therefore, to achieve stability and robustness of the estimates and to avoid bias in the scorecard, the development of the application scorecard considered all applications received by the lender, regardless of whether the application was accepted or rejected. Of the accepted applications, some were not taken up due to the issues of cold scoring. The taken up/non taken up model was developed to determine the likelihood of the rejected applications to take up the loan should it have been accepted. Further, a Known Good Bad (KGB) model was developed to assign inferred performance to the rejected applications through the reject inference process. The KGB model tracked the performance of the accepted and taken up population from the point of application to at least eighteen months in performance. This was done to generate the target variable and to assign weights to all the data including accepts and rejects used for the development of the scorecard. The SME application scorecard developed herein can be used to decide whether to extend credit to SMEs with an aim to reduce defaults and serious delinquencies on new applicants. In addition, the model can also be used to allocate capital, determine risk tendency and monitor the performance of SME credit portfolio.

5.3 Conclusion

The main aim of this study was to investigate the success rate of SME applications for commercial funding with an objective to assess the relationship between the demand and supply of credit against the credit market industry growth. From a risk rating perspective, the objective was to identify drivers of default and determine how the model is affected by introducing external information such as bureau data.

From the empirical investigation conducted, it can be concluded that there is a high positive correlation between the trends in the economy and accessibility to funding. The economic trends showed a decline in performance and so was the demand and supply of credit in the credit industry over time.

The robustness and stability of an SME application scorecard is enhanced by the inclusion of the rejected population as well as internal and bureau information. Through statistical comparison metrics discussed in Chapter 4, it can be concluded that this collective information can be used to establish drivers of default and develop an effective application scorecard as part of credit risk management. From the six variables selected in the final model it can be concluded that the fittest SMEs in accessing commercial bank loans have the following attributes:

a. operate in the services industry
b. have a long-standing rapport with the bank
c. keep excess to the minimal
d. keep active the transactional account with the bank
e. keep credit enquiries to the minimum
f. principal business owner should maintain a good credit record on all his loans

Indeed, the applicants who won't survive the lending criteria at bank include start-ups and young businesses as they do not have a long-standing relationship with the bank as a business.

The construction industry was scored with the least scorecard points showing that it is the riskiest industry in terms credit. This industry is labour and capital intensive. Production could have been hampered by power outages experienced in the review period because of operational issues at Eskom, the State-Owned Enterprise (SOE) power parastatal. Electricity shortages weighs down production and it makes it difficult for the industries to keep up with their financial obligations. This results in serious delinquencies on loans and hampers access to commercial bank finance to through the door applicants operating in construction.

5.4 Limitations of the Study

Following are the limitations of this study

- *Single product offering selection:* Customers can obtain credit through various bank product offerings including secured and unsecured term loans. This study is restricted to an unsecured transactional and revolving loan facility as this is the information approved for the research purposes and it provides the most substantial records.
- *Choice of variables:* Since the data was limited to a single product offering from a single financial institution, this influenced the choice of variables.
- *Regulatory Restrictions:* International legislation prevents the use of certain variables such as gender and population group in decision science. This is meant to prevent unreasonable prejudices (Hand & Henley, 1997). Classification should be based only on merit. Therefore, variables prohibited by law were not used in this study.
- *Limited to a single banking institution:* This investigation is depended on credit policies of a single financial institution. Due to the bureaucratic nature of the businesses and

issues of confidentiality, credit information from other financial institutions could not be obtained or used to draw solid, market wide conclusions.

- *Limited to an emerging market:* The study is based on information recorded in the South African emerging market and does not diversify into developed countries and frontier economies. The recommendations thus may just be limited to the South African market and may not explicitly be applicable elsewhere.

5.5 Recommendations

Based on the scorecard points allocation discussed in Chapter Four, start-ups and young businesses are recommended to frequently transact with commercial banks if loans are desired in future. The higher the transaction frequency, the higher the chance of accessing bank loans. Beyond transactions, SMEs are encouraged to establish strong networks and sound relationships with commercial banks as it becomes easier to obtain loans on the back of long-standing relationships. Further, the principal business owners are recommended to be vigilant with their financial obligations across the credit lending landscape as their creditworthiness, captured by the bureau information, has a huge bearing on access to commercial bank funding.

For future research, it is worthwhile incorporating various dimensions of product offerings, secured and unsecured lending, amortising and revolving products, to obtain a more holistic view of the behaviour of SME customers within the bank. Credit bureau institutions such as TransUnion and Experian have access to credit information from various banking and non-banking financial services institutions. It would be valuable for these bureaux to develop application scorecard bespoke to the SME credit market in emerging and frontier markets by consolidating this information to improve debt management, risk control and cost effectiveness.

SMEs form an integral aspect of most economies globally. Small businesses are inclined to foster innovative entrepreneurship and gratify a variety of socio-economic objectives such as poverty alleviation, income generation, employment creation and reduce societal inequalities. Findings from this study show that, the success of SMEs is largely dependent on the performance of the economy. The deterioration in economic growth observed in this study is in synchronisation with the country’s credit ratings. During the period under review, Fitch and Standard and Poor (S&P), the leading global credit rating agencies downgraded South Africa to the sub investment grade or junk status as the country notably fell into technical recession. With the elections behind the nation, the government is recommended to ratify policy reforms targeted at boosting economic growth. SMEs operating in the construction and manufacturing industries should be prioritised as these produce lucrative value-added products. Due to the labour-intensive nature of these industries, increased growth in such sectors can help mitigate the unemployment challenges. South Africa currently stands at an unemployment rate of roughly 27%, which is alarmingly one of the worst levels globally. Increased focus on SME growth helps mitigate the unemployment and social inequalities conundrum.

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APPENDIX A

Table 29: DTI Classification of SMEs in South Africa

Sector or sub-sectors in accordance with the Standard Industrial Classification	**Size or class**	**Total full-time equivalent of paid employees Less than:**	**Total annual turnover Less than:**	**Total gross asset value (fixed property excluded) Less than:**
Agriculture	Medium	100	R 4.00 m	R 4.00 m
	Small	50	R 2.00 m	R 2.00 m
	Very small	10	R 0.40 m	R 0.40 m
	Micro	5	R 0.15 m	R 0.10 m
Mining and Quarrying	Medium	200	R30.00 m	R18.00 m
	Small	50	R 7.50 m	R 4.50 m
	Very small	20	R 3.00 m	R 1.80 m
	Micro	5	R 0.15 m	R 0.10 m
Manufacturing	Medium	200	R40.00 m	R15.00 m
	Small	50	R10.00 m	R 3.75 m
	Very small	20	R 4.00 m	R 1.50 m
	Micro	5	R 0.15 m	R 0.10 m
Electricity, Gas and Water	Medium	200	R40.00 m	R15.00 m
	Small	50	R10.00 m	R 3.75 m
	Very small	20	R 4.00 m	R 1.50 m
	Micro	5	R 0.15 m	R 0.10 m
Construction	Medium	200	R20.00 m	R 4.00 m
	Small	50	R 5.00 m	R 1.00 m
	Very small	20	R 2.00 m	R 0.40 m
	Micro	5	R 0.15 m	R 0.10 m
Retail and Motor Trade and Repair Services	Medium	100	R30.00 m	R 5.00 m
	Small	50	R15.00 m	R 2.50 m
	Very small	10	R 3.00 m	R 0.50 m
	Micro	5	R 0.15 m	R 0.10 m
Wholesale Trade, Commercial Agents and Allied Services	Medium	100	R50.00 m	R 8.00 m
	Small	50	R25.00 m	R 4.00 m
	Very small	10	R 5.00 m	R 0.50 m
	Micro	5	R 0.15 m	R 0.10 m
Catering, Accommodation and other Trade	Medium	100	R10.00 m	R 2.00 m
	Small	50	R 5.00 m	R 1.00 m
	Very small	10	R 1.00 m	R 0.20 m
	Micro	5	R 0.15 m	R 0.10 m
Transport, Storage and Communications	Medium	100	R20.00 m	R 5.00 m
	Small	50	R10.00 m	R 2.50 m
	Very small	10	R 2.00 m	R 0.50 m
	Micro	5	R 0.15 m	R 0.10 m
Finance and Business Services	Medium	100	R20.00 m	R 4.00 m
	Small	50	R10.00 m	R 2.00 m
	Very small	10	R 2.00 m	R 0.40 m
	Micro	5	R 0.15 m	R 0.10 m
Community, Social and Personal Services	Medium	100	R10.00 m	R 5.00 m
	Small	50	R 5.00 m	R 2.50 m
	Very small	10	R 1.00 m	R 0.50 m
	Micro	5	R 0.15 m	R 0.10 m

Source: (PRESIDENT'S OFFICE, 1996)

APPENDIX B

Table 30: VAR Models - Demand for Credit

Model Parameter Estimates						
Equation	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Variable**
GDP	**CONST2**	-0.34780	0.41939	-0.83	0.4097	1
	AR1_2_1	-0.00293	0.01897	-0.15	0.8777	volume(t-1)
	AR1_2_2	1.58792	0.09154	17.35	0.0001	gdp(t-1)
	AR1_2_3	0.00305	0.00858	0.36	0.7230	overdrafts_and_loans(t-1)
	AR1_2_4	0.04138	0.11029	0.38	0.7086	credit_extended_to_houseolds(t-1)
	AR1_2_5	0.78221	0.74814	1.05	0.2993	prime(t-1)
	AR2_2_1	0.01138	0.01920	0.59	0.5553	volume(t-2)
	AR2_2_2	-0.69430	0.09184	-7.56	0.0001	gdp(t-2)
	AR2_2_3	0.00540	0.00900	0.60	0.5506	overdrafts_and_loans(t-2)
	AR2_2_4	-0.12830	0.11362	-1.13	0.2626	credit_extended_to_houseolds(t-2)
	AR2_2_5	-0.52591	0.71713	-0.73	0.4657	prime(t-2)
OL	**CONST3**	14.10442	7.86637	1.79	0.0772	1
	AR1_3_1	0.04959	0.35588	0.14	0.8896	volume(t-1)
	AR1_3_2	-0.67552	1.71690	-0.39	0.6951	gdp(t-1)
	AR1_3_3	1.35468	0.16101	8.41	0.0001	overdrafts_and_loans(t-1)
	AR1_3_4	0.89229	2.06865	0.43	0.6675	credit_extended_to_houseolds(t-1)
	AR1_3_5	-10.39426	14.03259	-0.74	0.4613	prime(t-1)
	AR2_3_1	0.19980	0.36018	0.55	0.5808	volume(t-2)
	AR2_3_2	1.23782	1.72253	0.72	0.4747	gdp(t-2)
	AR2_3_3	-0.57933	0.16885	-3.43	0.0010	overdrafts_and_loans(t-2)
	AR2_3_4	0.68445	2.13113	0.32	0.7490	credit_extended_to_houseolds(t-2)
	AR2_3_5	2.30352	13.45101	0.17	0.8645	prime(t-2)
PLR	**CONST5**	0.13514	0.04826	2.80	0.0065	1
	AR1_5_1	-0.00367	0.00218	-1.68	0.0975	volume(t-1)
	AR1_5_2	0.00496	0.01053	0.47	0.6390	gdp(t-1)
	AR1_5_3	-0.00027	0.00099	-0.27	0.7868	overdrafts_and_loans(t-1)
	AR1_5_4	0.00006	0.01269	0.00	0.9961	credit_extended_to_houseolds(t-1)
	AR1_5_5	1.56871	0.08609	18.22	0.0001	prime(t-1)
	AR2_5_1	0.00035	0.00221	0.16	0.8750	volume(t-2)
	AR2_5_2	-0.00087	0.01057	-0.08	0.9347	gdp(t-2)
	AR2_5_3	-0.00061	0.00104	-0.59	0.5598	overdrafts_and_loans(t-2)
	AR2_5_4	0.01098	0.01307	0.84	0.4036	credit_extended_to_houseolds(t-2)
	AR2_5_5	-0.62615	0.08252	-7.59	0.0001	prime(t-2)

Source: Estimates from research data, 2019

Table 31: VAR Models - Supply of Credit

Model Parameter Estimates						
Equation	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Variable**
GDP	**CONST2**	0.39120	0.27795	1.41	0.1636	1
	AR1_2_1	0.04280	0.03945	1.08	0.2816	acceptance_rate(t-1)
	AR1_2_2	1.63063	0.09321	17.49	0.0001	gdp(t-1)
	AR1_2_3	0.02364	0.06238	0.38	0.7059	overdrafts_and_loans(t-1)
	AR1_2_4	0.04529	0.08718	0.52	0.6050	credit_extended_to_houseolds(t-1)
	AR1_2_5	0.31581	0.72382	0.44	0.6639	prime(t-1)
	AR2_2_1	-0.05198	0.03998	-1.30	0.1977	acceptance_rate(t-2)
	AR2_2_2	-0.72650	0.09387	-7.74	0.0001	gdp(t-2)
	AR2_2_3	-0.01121	0.06075	-0.18	0.8541	overdrafts_and_loans(t-2)
	AR2_2_4	-0.05876	0.08955	-0.66	0.5138	credit_extended_to_houseolds(t-2)
	AR2_2_5	-0.41209	0.73051	-0.56	0.5744	prime(t-2)
OL	**CONST3**	1.11285	0.58230	1.91	0.0600	1
	AR1_3_1	0.01124	0.08264	0.14	0.8922	acceptance_rate(t-1)
	AR1_3_2	-0.35446	0.19527	-1.82	0.0737	gdp(t-1)
	AR1_3_3	1.34353	0.13069	10.28	0.0001	overdrafts_and_loans(t-1)
	AR1_3_4	0.06778	0.18263	0.37	0.7116	credit_extended_to_houseolds(t-1)
	AR1_3_5	-0.20276	1.51640	-0.13	0.8940	prime(t-1)
	AR2_3_1	-0.01836	0.08375	-0.22	0.8271	acceptance_rate(t-2)
	AR2_3_2	0.46447	0.19667	2.36	0.0209	gdp(t-2)
	AR2_3_3	-0.51267	0.12728	-4.03	0.0001	overdrafts_and_loans(t-2)
	AR2_3_4	0.12777	0.18761	0.68	0.4981	credit_extended_to_houseolds(t-2)
	AR2_3_5	-0.40815	1.53041	-0.27	0.7905	prime(t-2)
PLR	**CONST4**	0.05057	0.03250	1.56	0.1241	1
	AR1_4_1	0.00076	0.00461	0.17	0.8694	acceptance_rate(t-1)
	AR1_4_2	-0.00046	0.01090	-0.04	0.9667	gdp(t-1)
	AR1_4_3	-0.00716	0.00729	-0.98	0.3295	overdrafts_and_loans(t-1)
	AR1_4_4	0.00331	0.01019	0.32	0.7463	credit_extended_to_houseolds(t-1)
	AR1_4_5	1.64295	0.08463	19.41	0.0001	prime(t-1)
	AR2_4_1	-0.00324	0.00467	-0.69	0.4900	acceptance_rate(t-2)
	AR2_4_2	0.00308	0.01098	0.28	0.7798	gdp(t-2)
	AR2_4_3	0.00505	0.00710	0.71	0.4797	overdrafts_and_loans(t-2)
	AR2_4_4	0.00197	0.01047	0.19	0.8511	credit_extended_to_houseolds(t-2)
	AR2_4_5	-0.67168	0.08541	-7.86	0.0001	prime(t-2)

Source: Estimates from research data, 2019

APPENDIX C

Figure 13: Univariate Analysis