UNIVERSITY OF CAPE TOWN

Predicting Loan Defaults in Development Financing in South Africa

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By

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MASTER OF COMMERCE IN DEVELOPMENT FINANCE

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DECLARATION

I, …Petros Mandla Sibiya.........., hereby declare that I am aware that plagiarism is unacceptable in all its forms and levels. Therefore, I hereby present this dissertation as my own original work and further assert that this work or dissertation has never been submitted before to any institution or university for examination purposes towards obtaining a degree in any field of study.

Signature: Signed by candidate ……………………………………………….

Date: 17 March 2023 ……………………………….

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DEDICATION

This research is dedicated to my wife Nicolette Sibiya and my three sons Phumelele, Mnqobi, and Dominic Sibiya. Thank you for all the sacrifices and support since the beginning of this journey – it is much appreciated. I also dedicate the dissertation to my late father Enoch Sibiya who raised me and taught me a lot in life. Without his teachings and strong foundation, I wouldn't have reached this far in life. I love you "Baba Wami", life is not the same without you.

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Firstly, I thank Almighty God Jehovah, who is a creator of everything in the heavens and on earth, and I thank his beloved son Jesus Christ our Lord and Saviour, without whom I wouldn’t have come this far in life. I owe it all to Him and I will be forever grateful for the gift of life and all the blessings, opportunities and favours that were granted to me. Glory be to God! I love you endlessly.

To my supervisor Prof Latif Alhassan, thank you very much. Without your guidance and constructive advice, this study would not have been a success. Please accept my appreciation, Prof Latif, and stay blessed.

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ABSTRACT

Non-Performing Loans (*NPLs*) remain a pertinent issue faced by financial institutions, including Development Finance Institutions (DFIs). The escalation of this problem has a detrimental impact on the DFI's profitability and sustainability in the long-term, including hampering its crucial role in addressing the failures of the market mechanism to allocate financial resources to the development agendas of developing countries. This study examines the client and loan factors linked to the predictability of loan defaults in a DFI loan portfolio, using the secondary loan portfolio data of a major DFI from 2016 to 2021. The logistic estimation technique was employed to examine the effect of variables including firm industry, firm size, firm development stage, deal complexity, credit scoring, and type of financial instrument on default predictability of DFI loans.

The empirical findings of the study show that the size of the firm and the industry in which it operates, are client factors linked to the predictability of loan defaults in a DFI loan portfolio. The type of financial instrument, complexity of the deal, and the credit scoring represented characteristic loan factors that were investigated in this study. All three variables were found to be linked to loan default predictability. Some of the recommendations put forward for the consideration of management includes close monitoring of all clients in the loan book, offering business support to SMEs, and thorough due diligence process amongst others.

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LIST OF ABBREVIATIONS AND ACRONYMS

CAPM	Capital Asset Pricing Model
CAR	Capital Adequacy Ratio
CRM	Credit Risk Management
DBSA	Development Bank of Southern Africa
DFI	Development Finance Institution
DTIC	Department of Trade Industry and Competition
ECDC	Eastern Cape Development Corporation
FDC	Free State Development Corporation
FSCA	Financial Sector Conduct Authority
GEP	Gauteng Enterprise Propeller
GCC	Gulf Cooperation Council
GDP	Gross Domestic Product
GMM	Gaussian Mixture Model
IBM	International Business Machines
ICT	Information and Communication Technology
IDC	Industrial Development Corporation of South Africa
KMV	Kealhofer, McQuown, and Vasicek
LEDA	Limpopo Economic Development Agency
MEGA	Mpumalanga Economic Growth Agency
ML	Maximum Likelihood
NED	Non-Executive Directors
NEF	National Empowerment Fund
NHFC	National Housing Finance Corporation
NPLs	Non-Performing Loans
NURCHA	National Urban Reconstruction and Housing Agency
NWDC	North-West Development Corporation
OLS	Ordinary Least Squares
PAIA	Promotion of Access to Information Act
PIMD	Post Investment Monitoring Department
POPIA	Protection of Personal Information Act
RHLF	Rural Housing Loan Fund
ROA	Return On Assets
ROE	Return On Equity

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RWA	Risk Weighted Assets,
SBU	Strategic Business Units
SEFA	Small Enterprise Finance Agency
SME	Small Medium Enterprise
SOE	State Owned Enterprise
SPSS	Statistical Program for Social Science
VIX	Volatility Index
W&R	Workout and Restructuring

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Loan defaults particularly NPLs are a serious problem faced by financial institutions, due to their huge effect on profitability and long-term sustainability (Odegua, 2020; Scope, 1998; Munangi & Sibindi, 2020). DFIs often extend credit to companies based on information which includes the client's ability to demonstrate the economic viability of the business, and to a lesser extent on the availability of collateral. Due to their developmental mandate, DFIs operate differently from commercial banks. DFIs often undertake riskier projects and investments which commercial banks are not willing to fund. This suggest that DFIs are not profit driven and their funding activities are largely influenced by a country's economic growth and socioeconomic factors. Despite the differences between commercial banks and DFIs, there are similarities regarding how these financial institutions operate. Like the commercial bank, DFI funding applications go through various screening processes to determine their economic merit, but most importantly, to mitigate credit risk. However, NPLs continue to be a major problem on DFI balance sheets as they affect liquidity and the ability to raise capital for future investments. This is supported by Khan et al. (2020) who reported loss of interest revenue, reduced investments, liquidity crises, and bankruptcy problems as consequences of loan defaults. For this reason, it is necessary to identify factors that affect loan defaults, in order to lower the incidence of high NPLs and bolster the stability of DFIs in support of their economic goals.

Most of the research (Chelagat, 2012; Njeru et al., 2017; Kegninkeu, 2018; Ntiamoah et al., 2014) in this subject has focussed on commercial banks as opposed to DFIs. However, the causes of loan defaults are not the same across the various financial institutions (Ntiamoah et al., 2014), and hence cannot be generalised. Therefore, this study seeks to examine factors associated with the predictability of loan defaults in the context of a DFI. The study followed the approach of a case study, as the investigation is on a specific DFI which, for the purposes of this research, will be referred to as *The DFI*. This is in order to comply with the prescripts of the Protection of Personal Information Act (POPIA) and the Promotion of Access to Information Act (PAIA), which protects the organisation's name and its reputation (Blignaut, 2022). *The DFI* is a state-owned entity (SOE), and the sole shareholder is the South African government (Goga et al., 2019). *The DFI* is mandated to support the development of industrial

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capacity in the country and to create value over the long-term. *The DFI* is a self-funded organisation and relies on interest earned from loans as well as dividend earnings generated from existing investments. This means that even though *The DFI* is owned by the South African government, it does not depend on government support to fund its operations. The implications of NPLs at high levels in DFIs inevitably forces government to provide financial assistance from its already-strained budget. The sovereign credit rating agency, Moody's has in previous reports emphasised the need for South African State Owned Entities (SOEs) to be self-sustainable and economically viable entities to reduce their reliance on the state (Abrahams, 2015).

1.2 PROBLEM STATEMENT AND RESEARCH QUESTIONS

a) Defined problem of the study

The problem area that a study seeks to address is rising NPLs in *The DFI* loan portfolio as it signals a threat to the financial sustainability of the biggest DFI in South Africa. The average NPL ratio used as a standard reporting measure of credit risk and indicator of asset quality for the past five years, is 26% which is above the 15% industry norm (Asfaw et al., 2016). This postulates there is a problem of loan repayments or loan defaults by the clients funded by *The DFI*. The nature of the problem is not exclusive to *The DFI,* as Calice (2013) highlights that African DFIs have problematic asset qualities with NPLs' ratio exceeding 15% as reported by 52% of the institutions.

b) Research linked to the problem

According to Munangi and Sibindi (2020), credit risk proxied by NPLs is a major issue in South African finance institutions. Although domestic DFIs are not driven by maximization of profits in comparison to commercial banks, their financial sustainability is still absolutely essential in the delivery of the development finance (Abrahams, 2015). Pere (2021) highlights the trend of poor financial performance by South African DFIs as exhibited by significant losses and poor loan recoveries. Given their policy mandate, this suggests that DFIs could be underperforming in the alleviation of market failures and the advancement of social and economic development goals (Pere, 2021). The literature shows that most studies that have investigated NPLs have examined the issue from the perspective of both micro- and macro-economic factors, focussing on the commercial banking sector of countries outside the

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Republic of South Africa (Akter & Roy, 2017; Kumar et al., 2018). The research on the problem in the context of the DFIs is scant, and the closest research was accomplished by Asfaw et al. (2016) for the Development Bank of Ethiopia. Tsumake (2016) examined the influences of NPLs on the banking industry of Botswana, and Munangi (2020) investigated commercial banks of South Africa to determine the influence of credit risk on financial performance. In other words, studies have focussed on the banks' specific variables that influence NPLs. Not much work has been done on loan defaults predicting factors which are more forward looking, particularly examining borrower and loan characteristics variables in the context of the DFI. This research is intended to fill this gap and contribute meaningfully to the growing body of knowledge on the subject. The literature also indicates there is no standardised approach to investigating loan defaults or NPLs, as researchers tend to select variables on the basis of interest (Ali, 2013).

c) *The DFI* case

NPLs relating to *The DFI* loan portfolio are on the rise despite numerous, seemingly adequate, credit risk measures being put in place. The annual reported ratio of NPLs was 18% in 2017, 22% in 2018/19 and increased to 26% in 2020. In addition, the NPLs ratio further increased to 38% in 2020/21. Previous research (Ofonyelu & Alimi, 2013) link the high incidence of loan defaults or NPLs in financial institutions to inadequate assessment of credit risks. Therefore, the importance of analysing loan defaults of *The DFI* is underpinned by the essential role of DFIs through their various mandates, such as promoting South African economic growth and job creation. Failure to investigate and address the loan default problem and NPLs will have an adverse effect, including the weakening of *The DFI's* lending capacity and its ability to borrow for future investments. Moreover, consequences might even result in the bankruptcy of *The DFI* (Khan et al., 2020). Therefore, to maintain the financial soundness of *The DFI*, all loans extended to various sectors of the economy must be fully recovered timeously.

According to Asfaw et al. (2016) any form of credit default (random or due to unpredictable behaviours) has to be empirically investigated. This is to enable findings to be used to amend the credit programs of DFIs for the better and ensure long-term sustainability. Consequently, this study seeks to investigate factors linked to the predictability of loan defaults in *The DFI* loan portfolio.

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Based on the problem statement, the study seeks to provide answers to the following research questions:

- What characteristic loan factors are linked to the predictability of loan defaults in *The DFI* loan portfolio?
- What characteristic client factors are linked to the predictability of loan defaults in *The DFI* loan portfolio?

1.3 RESEARCH OBJECTIVES AND HYPOTHESES

1.3.1 Research objectives

The study aims to investigate factors that influence rising NPLs on *The DFI* loan portfolio. Specifically, the study aims to achieve the following research objectives:

- Identify loan characteristics linked to the predictability of loan defaults in *The DFI* loan portfolio.
- Identify client characteristics linked to the predictability of loan defaults in *The DFI* loan portfolio.

In line with the research objectives, policy recommendations for the effective management and reduction of loan defaults or NPLs will be provided, based on the research findings.

1.3.2 Research hypotheses

- **THE FIRST RESEARCH QUESTION:**
  What characteristic loan factors are linked to the predictability of loan defaults in The DFI loan portfolio?

Hypothesis 1A: Loan characteristics (*Type of Financial Instrument*)

Null Hypothesis (H1Ao): Type of financial instrument is not linked to the predictability of loan defaults.

Alternative Hypothesis ($H1A_1$): Type of financial instrument is linked to the predictability of loan defaults.

Hypothesis 1B: Credit scoring

Null Hypothesis (H1Bo): Credit scoring is not linked to predictability of loan defaults.

Alternative Hypothesis (H1B$_1$): Credit scoring is linked to predictability of loan defaults.

Hypothesis 1C: Deal complexity

Null Hypothesis (H1Co): Deal complexity is not linked to predictability of loan defaults.

Alternative Hypothesis (H1C$_1$): Deal complexity is linked to predictability of loan defaults.

- **THE SECOND RESEARCH QUESTION:**
  What characteristic client factors are linked to the predictability of loan defaults in The DFI loan portfolio?

Hypothesis 2: Client characteristics:

Firm development stage: Start-up / Growth / Matured

Null Hypothesis (H2Ao): Firm development stage is not linked to predictability of loan defaults.

Alternative Hypothesis (H2A$_1$): Firm development stage is linked to predictability of loan defaults.

Firm industry:

Null Hypothesis (H2Bo): Firm industry is not linked to predictability of loan defaults.

Alternative Hypothesis (H2B$_1$): Firm industry is linked to predictability of loan defaults.

Firm size:

Null Hypothesis (H2Co): Firm size is not linked to predictability of loan defaults.

Alternative Hypothesis (H2C$_1$): Firm size is linked to predictability of loan defaults.

1.4 SCOPE AND JUSTIFICATION OF STUDY

This study contributes to the growing research being conducted on DFIs regarding NPLs. In the context of this subject, many studies (Ahmad & Ariff, 2007; Haniifah, 2015a; Koju et al., 2018; Kumar et al., 2018; Wood & Skinner, 2018) have investigated the issue of NPLs in commercial banks outside South Africa. However, this does not suggest there's no South African studies in this field. Despite general lack of consensus across studies, to the best of this researcher's knowledge, there is limited research that has examined factors linked to the

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predictability of loan defaults or NPLs in the context of the DFIs in South Africa. The purpose of this research is to examine and analyse an existing problem of rising NPLs at the specific DFI, herein referred to as *The DFI*. Based on the research findings, appropriate recommendations will be made to *The DFI* management in order improve effectiveness of credit appraisals, and ensure better deal structuring, etc. There is also scope to contribute to the area of research as the issue of NPLs or loan defaults can be better understood in the context of DFIs based in South Africa. In addition, solving the persisting NPLs issue through applied research will be of great benefit to the South African community, because it results in financial stability of *The DFI*. Consequently, more investments can be undertaken for country's economic development and the creation of employment for citizens.

The scope of this study is limited to investigating the issue in one specific instance in South Africa, namely *The DFI,* and for this reason it does not investigate other domestic DFIs.

1.5 ORGANISATION OF STUDY

This research consists of five chapters structured as follows:

Chapter 1 is the introduction of the study providing the context of the background, problem statement, research questions, study objectives and hypotheses.

Chapter 2 presents the literature review. First, it discusses the relevant theories underpinning the research, followed by the empirical literature review.

Chapter 3 discusses the research methodology and includes the research approach, and research design covering sampling techniques and the data collection method, and a statistical analysis technique applied to test the hypotheses.

Chapter 4 presents the results and provides an in-depth discussion of the empirical findings.

Chapter 5 concludes the study with the recommendations based on the findings.

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CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

This chapter encompasses the definition of the main terms for the study, followed by an overview of the DFIs in South Africa. The theoretical background of the study is presented followed by a review of the empirical research previously undertaken in order to assess both micro and macroeconomic factors affecting NPLs in financial institutions. The chapter ends with a conclusion encapsulating the key findings on the research subject based on the reviewed literature including the identification of the research gap.

2.2 DEFINITION OF TERMS OR CONCEPTS

a) Development finance institutions (DFIs)

DFIs are by and large state-owned institutions that were founded to deliver broad developmental goals. These include investment in various infrastructure projects and private entities, with the aim of stimulating the country's economic growth and creating employment for citizens (Mudaliar et al., 2016). To achieve their social and economic goals, DFIs often channel credit at concessionary terms to fund priority sectors believed to have been abandoned by commercial banks due to variety of reasons. For example, in contrast to banks the DFIs are doesn't reject a viable investment due to lack of security and tend to have high risk appetite driven by specific mandate. The banks might not have an appetite to invest in a new technology high risk projects which has not been commercialised (Yaron, 1992). The interest rates charged by DFIs are risk-based and hence are generally higher than offered by the banks. The loan tenure varies depending on the purpose of the loan (i.e., CAPEX, Working Capital, Guarantees, etc.). Due to their role in dealing with market failures, the DFI's assessment has not always been easy, since their performance valuation goes beyond the standard financial profitability ratios applied in the commercial banking sector. According to Qunta (2015) the DFIs would prioritise projects and sectors where social benefits exceed commercial ones. The DFI's key performance indicator includes reporting annually on development impact made in areas of job creation, investments on youth & woman owned businesses, transformation / Black Economic Empowerment, infrastructure development amongst others. There are number of DFIs domestically, but there are also those that transcend national borders. These have invariably been constituted by governments to fulfil different mandates, but they are also essential in the provision of counter-cyclical lending. The role of the DFI has evolved over time and most have

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expanded on their original mandates to deal with the pertinent socioeconomic issues of their respective countries (Nkosi, 2017). Some DFIs are self-funded and doesn't receive grants from the state and hence must be financially sustainable to carry out their mandates. Others rely on government for financial support.

b) Non-Performing Loans (NPLs)

In general terms NPLs are defined as loans that are not repaid by the borrower over a ninety-day period (Wood & Skinner, 2018). The category of NPLs is comprised of default loans, distressed loans, and bad loans. It is worth noting that there are disparities between countries and financial institutions on the designation of loans as non-performing. In some countries it suggests impaired loans, while in others it refers to the payments that are past due (Molyneux, 2017). This suggests that the designation criteria of NPLs is discretionary. NPLs represent credit risk, which is determined as a ratio against total DFI loans. The NPL ratio is associated with the asset quality which is key in the banking or finance industry. The literature suggests high levels of NPLs are behind the collapse of the finance industry. Consequently, since the 2008 financial crisis, understanding the determinants of NPLs has gained prominence in the risk management function of financial institutions (Ozili, 2019). Furthermore, NPLs and loan defaults can be used interchangeably (Molyneux, 2017), and Agbemava et al. (2016) posit that defaulted loans are in violation of the loan agreement, as payments of capital and interest are not made when they are due. The focus of this study is on loan defaults predictability particularly the NPLs.

2.3 OVERVIEW OF DFIs IN SOUTH AFRICA

DFIs are generally instituted by governments to deal with market failures by augmenting market finance and the resources of the government. Currently, however, the role of DFIs has gone beyond addressing market failures. It has done this through the provision of development finance, playing a huge role in job creation, the development of private sector, import substitution, the development of historically disadvantaged groups and less developed regions, amongst other undertakings (Gumede et al., 2011). It thus stands to reason that various DFIs (e.g. domestic DFIs, regional DFIs, bilateral and multilateral DFIs), differ in size, mandate, scope, and geographical reach. According to Goga et al. (2019) the Republic of South Africa has approximately sixteen DFIs comprising of national (NDFIs) and provincial (PDFIs) bodies, as depicted in Table 1 below.

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Table 1. South African DFIs at national and provincial level (Goga et al., 2019)

National Development Finance Institutions (NDFIs)	**Provincial Development Finance Institutions (PDFIs)**
Development Bank of South Africa (DBSA)	Eastern Cape Development Corporation (ECDC)
Industrial Development Corporation (IDC)	Eastern Cape Rural Development Agency (ECRDA)
Land and Agricultural Development Bank of South Africa (Land Bank)	Free State Development Corporation (FDC)
National Empowerment Fund (NEF)	Gauteng Enterprise Propeller (GEP)
National Housing Finance Corporation (NHFC)	Ithala
National Urban Reconstruction and Housing Agency (NURCHA)	Limpopo Economic Development Agency (LEDA)
Rural Housing Loan Fund (RHLF)	Mpumalanga Economic Growth Agency (MEGA)
Small Enterprise Finance Agency (SEFA)	North-West Development Corporation (NWDC)

Given the size and mandate of *The DFI* which is the subject of this study, this section covers the major national DFIs in the country. According to Gumede et al. (2011), at a national level, South Africa's four major DFIs comprised the DBSA, IDC, NEF and Land Bank. Table 2 depicts the prominent DFIs in South Africa according to their mandate and asset size. State-owned entities (SOEs) are classified in terms of the Public Finance Management Act (PFMA) which prescribes the form of financial assistance the SOEs could obtain from the government or National Treasury. Consequently, some SOEs are not eligible for any form of funding from the state and hence all their financial liabilities must be financed from operational revenue (Deparment of National Treasury, 2021). The IDC, Land Bank, and DBSA are categorised as Schedule 2 entities, implying they are major public entities that are financially independent of the state finances (i.e., National Revenue Fund, taxes or other statutory money) to deliver their respective mandates (Goga et al., 2019).

Table 2. Major Development Finance Institutions in South Africa

Development Finance Institutions at national	**Established**	**PFMA Classification**	**Assets (R' mil) FY21**	**Mandate**
Industrial Development Corporation (IDC)	1940	Schedule 2	147 429	To promote Industrialisation
Development Bank of Southern Africa (DBSA)	1983	Schedule 2	100 048	Infrastructure Development
Land Bank (Landbank)	1912	Schedule 2	40 166	To support Agriculture
National Empowerment Fund (NEF)	1998	Schedule 3A	4 578	To support the Black Empowered Businesses

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National Housing Finance Corporation (NHFC)	1996	Schedule 3A	To ensure that every South African with a regular source of income can gain access to finance, to acquire and improve a home
National Urban Reconstruction and Housing Agency (Nurcha)	1994	Schedule 3A	To supports the national programme to house all South Africans in sustainable human settlements
Rural Housing Loan Fund (RHLF)	1996	Schedule 3A	To provide loans, through intermediaries, to low-income households for incremental housing purposes
Small Enterprise Finance Agency (SEFA)	2012	Schedule 3A	To foster the establishment, survival, and growth of SMMEs and cooperatives

Source: Extracted from annual reports

A summary of the main DFIs in South Africa

The Development Bank of South Africa (DBSA) was established in 1983 and its mandate concerns the provision of critical social and economic infrastructure. The DBSA is continuously broadening its geographical reach and undertaking infrastructure projects in sectors such as energy, healthcare, water and sanitation, and transport, amongst others. This applies particularly to the Southern African region, but it also reaches into the rest of Africa.

The National Empowerment Fund (NEF) supports mostly black-owned businesses, from early-stage start-ups or franchises to large-scale multi-million (USD) projects. The NEF was established in 1998 through an Act of Parliament (Act 105 of 1998). Unlike DBSA and IDC, the NEF is fully financed by government through taxes or other statutory money. This is in accordance with category 3A of the Public Management Finance Act (PMFA) in terms of classification of entities (Goga et al., 2019).

The Land Bank, founded in 1912, is the oldest South African DFI that supports agricultural businesses and farmers. This includes new entrants and historically disadvantaged farmers to large scale commercial farming projects (Mudaliar et al., 2016).

The funding instruments used by DFIs vary and comprise of normal loan (debt), equity, quasi-equity, or mezzanine financing depending on the transaction's financing needs or the project size. Some DFIs have sovereign backed balance sheets while others such as the IDC are self-funded with no financial support from the government. Nonetheless, DFIs driven by their developmental mandates often invest in high-risk projects with less focus on profitability when compared with commercial banks (Goga et al., 2019).

The Industrial Development Corporation of South Africa (IDC) is one of largest the national DFIs in South Africa and since 1940 has been instrumental in promoting the country's industrial policy. The role of the IDC is to enhance the industrial capability of South Africa, and the rest of the continent, thereby supporting economic growth and industrial development (Abrahams, 2015; Goga et al., 2019).

As per its developmental mandate, *The DFI*'s activities extend to various sectors of the economy including mining, agriculture, textiles, chemicals, industrial infrastructure, Information and Communication Technology (ICT) and media, tourism, etc. *The DFI* provides lending predominantly to manufacturing entities (SMEs, Large Enterprises, Government, and other DFIs) and this includes funding start-ups, acquisitions, and expansions for existing companies. *The DFI*'s business and funding activities are summarised and presented in Table 3.

Table 3. *The DFI* business and funding activities

Activities	Customers	Business lifecycle	Sectoral involvement	Funding products	Regional involvement
• Provision of development finance • Project development • Research and policy inputs • Development of an enabling environment and strategic partnerships • Fund management • Business Support • Capacity building	• Business segmented: Small, Medium, Large • Government • Other DFIs	• Conceptual • Pre-feasibility • Feasibility • Product commercialisation • Establishment • Expansion • Mature • Distressed business	• Metal beneficiation and mining • Agro-processing and agriculture • Upstream and downstream chemicals • Clothing and textiles • Tourism, ICT and media • Other manufacturing industries including heavy manufacturing • Industrial infrastructure • New industries	• General debt • Quasi-equity • Equity • Export/import finance • Short-term trade finance • Bridging finance • Guarantees • Lines of credit • Syndication and lead arranging	• South Africa • Rest of Africa • Global exports of South African goods

Source: (*The DFI*, 2021)

The DFI's funding model depicted in Figure 1 shows that it is self-funded and thus does not rely on the government for financial support to carry out its mandate. *The DFI* uses the strength of its balance sheet (i.e. retained earnings / borrowings) to finance entities in various sectors

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and generate revenues from the loan interest repayments, dividends from equity investments, and capital raised from its matured investments (*The DFI*, 2019).

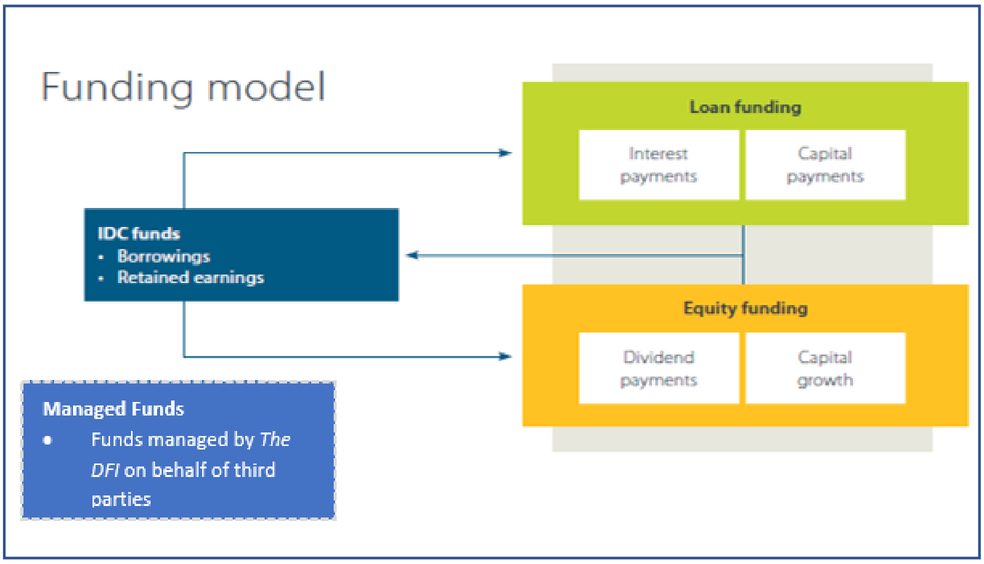

Figure 1. *The DFI* Funding Model (*The DFI*, 2021)

As presented in figure 1, *The DFI* is also administering third party (i.e. Department of Trade, Industry and Competition) funds which are used to supplement its strategies or developmental mandate, i.e. employment creation, increasing local manufacturing competitiveness, empowerment of youth and women, supporting black industrialists, etc. Moreover, the third-party funding schemes that are managed by *The DFI* enables blended financing or concessional funding in terms that are more favorable than normal *DFI* funding interest rates or pricing as determined by a risk management department. Depending on the business needs, *The DFI* uses various funding instruments comprising of normal loans, quasi-equity (i.e. a combination of debt and equity), short-term trade finance, bridging finance, export or import finance, and guarantees.

According to Appiah (2015), a loan portfolio is an important asset of any financial institution as it represents the source (s) of generated revenues. *The DFI* provides a moratorium period and flexible loan repayment terms, enabling entrepreneurs or funded companies to service the loan repayments, both capital and interest. However, despite the various efforts undertaken during deal structuring, most of *The DFI* loans are still impaired or end up in default. In contrast to commercial banks, *The DFI* has a workout and restructuring (W&R) unit to assist and support clients that are in financial distress. This role of *The DFI* is aimed at ensuring the creation of sustainable businesses and employment through business turnaround strategies

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crafted specifically for each case. In general, interest rates on *The DFI's* loans are not competitive in comparison to those offered by commercial banks. This is attributed to the fact that *The DFI* is often a last resort lender and is apt to consider applications of clients that do not qualify for private sector funding, or that have been turned down by commercial banks. This suggests that *The DFI* should be rewarded for taking on higher risk (Goga et al., 2019).

NPLs are used as an indicator of credit risk and to measure the asset quality of financial institutions. Furthermore, failures of financial institutions have been linked to NPLs (Tsalas & Nikolopoulos, 2017). For this reason the importance of monitoring and controlling NPLs has received major attention in the banking industry following the global financial crisis in 2008/09 (Akinlo & Emmanuel, 2014). In addition, examining factors that affect NPLs has received the attention of researchers and banking authorities as they seek to maintain stability in the banking sector. NPLs can result from a variety of factors and the available literature has categorised these into macroeconomic conditions (exogenous factors) that may affect a borrower's capacity to honour their debt obligation, and microeconomic / lender-specific factors that are deemed to be within the control of management (Tsalas & Nikolopoulos, 2017; Laryea et al., 2016). The effects of both micro- and macroeconomic factors on NPLs are explained by researchers using various theories. However, factors that have been researched at the firm, regional, and country levels have yielded an inconsistency in the findings. This suggests that the impact of NPLs differs by financial institution, based on the region, and by the country.

2.4 THEORETICAL FRAMEWORK

In this section the existing relevant theories on the subject are examined, as are various studies that have been undertaken to explain the issue of NPLs in financial institutions. From this perspective, the theory review below provides key insights on the issue being investigated from which the justification of loan defaults and NPLs determinants can be derived.

2.4.1 Portfolio theory

The portfolio theory is based on the work of Markowitz (1952) who demonstrated that investment in portfolios made by rational investors is based on the overall risk and expected returns. In the context of portfolio theory, risk is explained by variability, or standard deviation of return on a given asset. Standard deviation of return is thus used as a measure of volatility. Consequently, portfolio theory suggests the efficient diversification of an investment portfolio

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to reduce the levels of unsystematic risk associated with the expected return. Portfolio theory posits that there is a portfolio which gives both maximum expected returns and minimum variance, and recommend this portfolio to the investor. However, risks that are systematic, i.e. inherent in the market, cannot be eliminated or diversified away (Markowitz, 1952; Ocran, 2012; Mutua & Gekara, 2017). The systematic risk facing commercial banks and DFIs is largely influenced by the economic performance in domestic economies (Kumar et al., 2018). Given the higher risks taken by DFIs to fund riskier projects that banks do not have the appetite for, most expect to be compensated - hence the cost of funding by DFIs is often higher than in commercial banks. This is in line with the principle of portfolio theory.

Based on portfolio theory financial institutions should follow a risk-averse approach by diversifying their loan portfolios to maximise returns. In contrast, corporate finance theory propounds that firms will enjoy cost reduction benefits when concentrating their activities on specific sectors that they have expertise in (Chen et al., 2013). This is prominent with DFIs as some tend to pinpoint specific sectors of the economy in line with their developmental mandate. This business model also results in sector concentration risk which DFIs must manage. Moreover, it also affects the loan pricing as some industries are deemed to be riskier than others.

2.4.2 Theory of Capital Asset Pricing Model (CAPM)

The theory of CAPM was pioneered by Sharpe (1964), Lintner (1965) and Mossin (1966) on the foundation of Markowitz' (1952) Portfolio Theory. CAPM explains the relationship between risk and return under a set of assumptions including an efficient capital market. Because there is a view that all investors borrow and lend at one risk-free rate of interest, CAPM theory suggests that the optimal approach in investing is to distribute the portfolio between the market portfolio and the risk-free investment. The key element of the model is the separation of risk between unsystematic, company-specific risk and systematic risks resulting from uncertainty in market conditions (Rao, 2003).

The relevance of Portfolio and CAPM theories in financial institutions lies in the credit risk management whereby loan portfolios are diversified in terms of exposure and across borrowers. The applicability of CAPM theory is when financial institutions evaluate and undertake investments based on expected returns and diversification of risk. However, both CAPM and

Portfolio theories have been criticised for unrealistic assumptions in the market. For example, the market for financial assets is not perfect and it is unlikely that all investors borrow and lend at one risk-free rate of interest, which is what CAPM has assumed. For this reason, due to imperfections in the market, the NPLs and loan defaults arise due to various factors which include Asymmetry Information, Moral Hazard, and more.

2.4.3 Moral Hazard Hypothesis

Keeton and Morris (1987) as quoted by Klein (2013) suggested that moral hazard motives are driven by financial institutions with low capital that increase the riskiness of their portfolio. This results in an increase in NPLs. Moral hazard occurs when one party enter a risky position knowing that it's fully protected against any financial loss, and all the costs are incurred by another party. This happens due to incomplete information between parties that are transacting with each other (Ocran, 2012b). Klein (2013) mentions that Keeton and Morris (1987) illustrated that banks with a low equity to asset ratio suffered excess loss rates. This hints that banks taking higher risks or indulging in excessive lending are exposed to higher losses. This was linked to lender-specific factors, as it is within the management control (Klein, 2013).

2.4.4 Credit Risk Theory

Credit risk theory was formally introduced by Melton (1974) who theorised that a relationship exists between a firm's capital structure and its ability to service the loan in terms of repayments on capital and interest. This theory suggests that financial institutions should ensure loan repayments are achievable through proper screening processes of the borrower (Mrindoko et al., 2020; Musa & Nasieku, 2019). Prior to Melton's (1974) theory, credit risk was not widely researched despite its impact on individuals, businesses and the financial sector. Historically, there was high dependency on actuarial methods to determine credit risk and the shortfall of actuarial methods was reliance on historical data. However, other quantitative methods introduced to determine credit risk included a structural approach, a reduced form appraisal, and an incomplete information approach (Mabonga and Kimani, 2017; Mutua & Gekara, 2017). Musa and Nasieku (2019) mentioned that credit risk theory is the most important, as it places emphasis on continuous monitoring of borrower creditworthiness to ensure adherence to the credit contractual terms.

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2.4.5 Credit Rationing Theory

Credit rationing is explained by Ocran (2012) as a mismatch between demand and supply of credit from lenders at the prevailing interest rate. The credit rationing theory of Stiglitz and Weiss (1981) posited that there was no price discrimination in the credit market due to asymmetric information. Consequently, financial institutions resort to charging higher interest rates as they are unable to distinguish between good and bad borrowers and hence, adverse selection. The adverse selection situation often chases away good borrowers who exit the market while the lenders are left with bad borrowers who, due to higher interest rates, undertake riskier projects (see Moral Hazard above). Therefore, it has been argued that credit rationing increases the probability of loan defaults. The rationale is that lender's expected returns for a given loan amount is determined by a contractual interest rate and the probability of repayment (Swank, 1996; Ocran, 2012).

According to Swank (1996) financial institutions, in particular, commercial banks insist on collateral in addition to higher contractual rates, in order to mitigate against the risk of default by the borrower. It has been suggested that the collateral requirement by banks reduces the effect of moral hazard as discussed above. However, collateral requirement also results in an adverse selection similar to loan interest rates. Previous studies have mentioned imitations of the credit rationing theory, suggesting that it could be based on a misguided view of lender inability to distinguish between riskier and non-riskier borrowers. It has been argued that banks have invested in technology and perform screening to obtain credit profile or information on the borrower prior providing credit. Song and Zhang (2018) supported and mentioned that through effective screening by banks and the provision of securitised loans, adverse selection and moral hazard issues can be effectively suppressed. However, results between collateralised loans and those in which no collateral was provided regarding a loan defaults risk, were not significant.

Generally, most start-up businesses and SMEs are excluded due to a lack of collateral and several other factors – see the 5Cs of Credit assessment by commercial banks. The 5Cs of credit entail the assessment of borrowers' general conditions, collateral availability, repayment capacity, character judgement based on credit history, and capital contribution towards an investment (Segal, 2022). However, in the case of *The DFI,* security is taken provided it is available, but *The DFI* will not reject an applicant due to lack of collateral if the business displays economic merits.

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2.4.6 Bad Luck Hypothesis

According to Berger and DeYoung (1997) as quoted by Klein (2013), the causality of NPLs is under certain circumstances attributed to “bad luck” mainly due to macroeconomic conditions. In addition, this theory posits that NPLs are likely to increase because of poor management practices such as poor loan underwriting, monitoring and control. Therefore, poor low-cost efficiency is deemed to be a signal for poor management practices, as proven by previous studies in the United States commercial banks for the period 1985 to 94 (Klein, 2013).

2.4.7 Skimping Hypothesis

Berger and DeYoung (1997), as quoted by Klein (2013), suggested their “Skimping Hypothesis” as an alternative hypothesis to show positive causality between NPLs and high cost efficiency. In terms of the skimping hypothesis, future NPLs result from fewer resources being allocated to the monitoring of lending risks. This is also attributed to poor management practices, as has been proven through previous research undertaken by Rossi, Schwaiger, and Winkler (2005) as quoted by Klein (2013).

2.5 CREDIT RISK MANAGEMENT (CRM) IN FINANCIAL INSTITUTIONS

As depicted in Figure 2, DFIs are faced with a variety of risks, including market and credit risks. It can be noted from the chart that risk exposure could arise both internally and externally of financial institutions. Macroeconomic risks, such as interest rates, foreign exchange, equity and commodity price risks, are outside the control of financial institutions, but transaction and portfolio concertation risks are within the control of the DFIs.

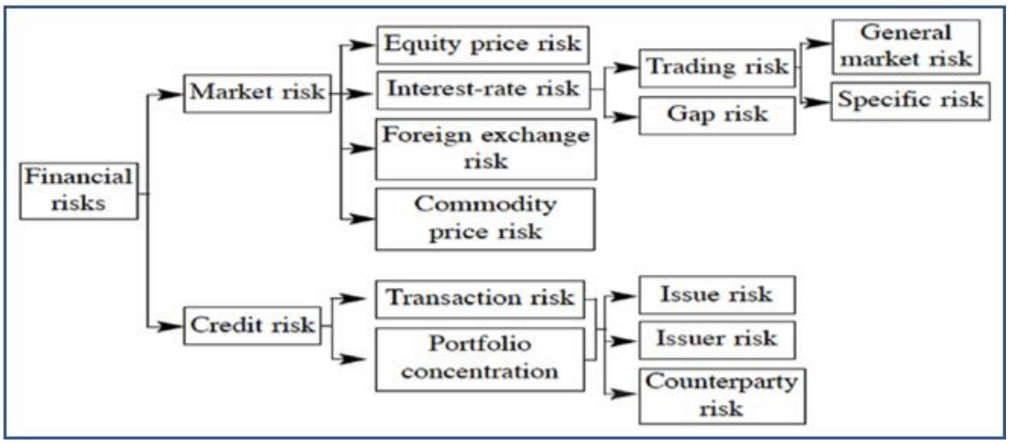

Figure 2. Various risks that DFIs and Banks are exposed (Ocran, 2012)

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Turning to *The DFI*, the credit risk management process entails a multi-disciplinary approach incorporating the following:

- The Strategic Business Unit (SBU) core due diligence team comprised of marketing, financial and technical disciplines. This SBU team is supported by legal, Environmental Health & Safety and technical services/valuations department.
- The Risk Management department is also involved in the due diligence process to perform an independent credit risk assessment.
- Final credit approvals are done by *The DFI* executives supported by independent non-executive directors (NEDs).
- The Post-investment Management (PIMD) unit is responsible for client loan portfolio management from the 1st funding disbursement until *The DFI* loans are fully repaid.
- Lastly, the W&R department becomes involved in cases of clients that experience cash-flow problems in order to assist with deal restructuring and/or turnaround strategies and supervision, until achieving profitability levels of the funded entities.

Credit risk affects all financial institutions (Ochieng, 2015). Credit risk as defined by *The DFI* refers to the potential losses on loans, advances, guarantees, quasi-equity and equity investments due to default. The source of credit risk at *The DFI* is primarily lending activities (*The DFI*, 2019). Most DFIs in South Africa are not really governed by the Basil Committee framework (i.e. Basil I, II, and III), which aims to strengthen the regulation, supervision and risk management of banks. This is due to the fact that DFIs are not deposit-taking, and hence, most follow the Basil Accord framework on voluntarily. Akwaa-Sekyi and Bosompra (2015) argue that reliance on the risk-based approaches does not solve the loan default problem. Chelagat (2012) asserts that credit risk has a severe impact on financial institutions and supersedes any other risks. Previous research has found credit risk to be positively correlated to the profitability of banks (Munangi & Sibindi, 2020).

According to Song and Zhang (2018), financial institutions such as banks and DFIs perform a screening process first relying on enterprise-audited financial statements and other soft information in order to determine the economic strength of the business and its ability to service the loan in terms of capital and interest repayments. Normally, this is done through a credit scoring mechanism to indicate the risk level of an applicant. As a requirement by the Basil framework, financial institutions need to be able to identify and analyse all risks via a Credit Risk Management function. This should be followed by proper monitoring to ensure risk

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management practices are aligned and that supervision occurs through an internal auditing process. A sound credit risk management is built upon good portfolio asset quality (Nyamwange, 2010).

With reference to portfolio concentration as shown in Figure 2, DFIs are highly exposed to sector concentration risk by virtue of their mandates. Concentration risk results from uneven distribution of credit exposure to specific industries and, if not properly managed, may result in high unexpected losses and insolvency issues. One of the methods used to deal with sector concentration risk is through the establishment of sector concentration limits and the monitoring and analysis of these (*The DFI*, 2018). However, there is no general methodology of dealing with the issue of sector or industry concentration risk.

2.6 FACTORS AFFECTING NON-PERFORMING LOANS

According to Amin et al. (2021) the influence of microeconomic (i.e. unsystematic) and macroeconomic (i.e. systematic) variables on credit risk incorporating NPLs has been theorized and tested through various studies. However, the evidence suggests that conclusions in different parts of the world, where studies have been undertaken, have not always upheld the common view among researchers. Therefore, this section examines the empirical literature on the factors that affect NPLs in financial institutions. This will assist in gaining insights on what has been done in the past in this subject and help identify the knowledge gap in order to shape the direction of this study.

2.6.1 Microeconomic (i.e. Lender- and Borrower-specific) determinants of NPLs

Loan defaults and NPLs result from many factors which could be grouped into borrower, lender, and loan characteristics. Borrower characteristics have been identified to be significant in predicting loan defaults (Akwaa-Sekyi & Bosompra, 2015; Chelagat, 2012).

According to Kumar et al. (2018) lender-specific characteristics are those that are within management control. These include return on assets (ROA), solvency, interest rates on loans, operating efficiency, and capital adequacy. Kirui (2014), as cited by Koju et al. (2018), employed a multi-regression model to examine the effect of NPLs on the profitability of commercial banks in Kenya for the period 2004 to 2014. The findings showed that NPLs reduce profitability (ROA) of banks. Khan et al. (2020) affirms this relationship and posits that financial institutions with high ROAs are in a stable position and management is not under pressure to support riskier loans in order to generate or increase revenue. Other studies delivered contrasting findings that ROA did not influence NPLs (Onyango & Olando, 2020).

By using three techniques of regression analysis, including the pooled ordinary least squares (OLS), random effects, and the fixed effects, Kumar et al. (2018) investigated the determinants of NPLs in small developing economies and used the Fiji banking sector as a case study. The statistically significant factors of NPLs identified were bank-specific including Return on Equity (ROE), solvency and size. ROE, like ROA, is also a measure of profitability, but is calculated based on shareholders' equity instead of assets. The relationship between ROE and the dependent variable NPLs was found to be negative. This suggested that less capitalised financial institutions incorporate inherent risk and are prone to high NPL levels. Consequently, high levels of NPLs lowers gross profits and thus ROE due to making provisions. High negative correlation implies weak debt management or, alternatively, exaggerated targeted profit goals and attributed to "bad luck". Conversely, high ROE and a low NPL ratio is linked to "good luck" for a financial institution (Kumar et al., 2018).

Wood and Skinner (2018) posited a capital adequacy ratio (CAR) which measures the solvency of a financial institution and its ability to absorb risks (i.e. unexpected losses) to have a positive influence on NPLs. This is because financial institutions with a higher CAR might increase lending scope and undertake riskier investments. This is applicable to DFIs as they often fund projects, such as infrastructure projects, unproven technologies, and others, which commercial banks do not have the appetite for, and hence, there is a high probability of increase in NPLs. Conversely, due to moral hazard, management actions might lead to excessive lending in risky investments with the aim of increasing profitability, and in turn increase NPLs. In order to prevent insolvency of financial institutions, the Basel Accord provides guidelines and insists that bank supervisory bodies set the capital adequacy ratio (CAR) as a tool to control excessive risk taking by banks or financial institutions (Laryea et al., 2016). However, *The DFI* is not regulated like commercial banks in terms of the Basel Accord framework, since it is not deposit-taking.

In addition, other bank-specific factors which have been linked to NPLs include size, efficiency, credit terms, and market power (Messai & Jouini, 2013). The Firm size represented by the total assets has been found to have negative influence on the NPLs (Pradhan & Pandey,

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2018). This proposes that large financial institutions have better strategies to manage loan portfolio risks as opposed to smaller banks. On the contrary, Rajha (2017) cited that large financial institutions tend to have a high rate of NPLs due to excessive risk-taking attributed to a “Too big to fail hypothesis”. This hypothesis contends that large banks experience high rates of NPLs because of too much leverage and the financing of low-quality borrowers.

According to Kumar et al. (2018) efficiency or inefficiency in financial institutions is measured in terms of operating expenses against the operating income ratio. In the context of NPLs, the positive relationship indicates a sign of bad management or resource wastage, while a negative correlation suggests efficient management of NPLs. Onyango and Olando (2020) assert that the operating inefficiency of financial institutions includes laxity in monitoring of credit portfolios during the loan term. The higher operational efficiency in banking is negatively associated with NPLs due to better credit management. Efficiency in banking involves achieving increased profitability with low operating costs. This suggests a negative relationship between ROA and operating expenses (Bandaranayake & Jayasinghe, 2014).

Research by Agbemava et al. (2016) found that loan type, credit appraisal, and collateral were statistically significant in the prediction of NPLs. Ahmad and Ariff (2007) support the finding that collateralised loans have a higher probability of default. From this finding it has been concluded that proper credit assessment is not adequately performed due to the availability of collateral which covers the risk exposure of the lender. However, Song and Zhang (2018) investigated Chinese unlisted SMEs from 2010 to 2013 and the findings showed that there is no significant difference between unsecured credit loans and collateralized loans in terms of loan defaults. Their study results showed that the default risk for third party-guaranteed loans was higher.

Africa (1995) concluded that existing clients previously funded by the DFI are less likely to default due to the already established relationship. This suggests that new clients are prone to default when granted credit by DFIs. In contrast, Ahmad and Ariff (2007) argued that established long-term relationship between clients and financial institutions is likely to increase NPLs, due to the changes in the credit risk profile of clients depending on specific circumstances. In addition, loan size was found to have no significant relationship on NPLs (Kuhn & Darroch, 1997).

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The study of Chelagat (2012) deduced that different types of loan have a variable influence on loan defaults and NPLs depending on their weighting. Akwaa-Sekyi and Bosompra (2015) suggest ownership or a business' legal structure could determine the loan default probability and referred to sole proprietorships as more prone to defaults when compared to other entity structures. This is because sole proprietorship entities are often run by one individual with no legal distinction between the owner and the business. However, Murthy and Mariadas (2017) link repayment defaults to borrower-specific sector or industry. Scope (1998) and Khan et al. (2020) contrasted this by mentioning that loan defaults are significant if screening mechanisms are weak, transforming DFIs to be welfare organisations. Appiah (2015) and Hoque and Hossain (2008) mentioned that higher interest rates or cost of debt are possible causes of loan defaults and NPLs. DFIs often charge higher interest rates which are justified by significant risks in funding investments or projects that banks are not willing to consider. However, special funding schemes are applied by DFIs to mitigate this effect and to support their developmental mandate, as opposed to profit maximisation.

2.6.2 Macroeconomic determinants of NPLs

In contrast to the lender-specific factors, there are also macroeconomic (systemic) / exogeneous factors that can contribute to an increase in NPLs of DFIs and banks. These include the real rate of GDP, inflation rate, exchange rates, and the political climate, among others (Haniifah, 2015b). The GDP growth as a measure of economic activity in the country is expected to be negatively related to NPLs, due to a favourable economic climate for businesses, and the availability of income to service the loan. This is supported by Messai and Jouini (2013) who mentioned that high levels of bad debt are prevalent during a period of economic contraction, i.e. a slump in GDP.

The relationship between NPLs and the lending rate / interest rate is positive since higher interest increases the cost of debt. Beck et al. (2013) asserts that NPLs increase due to depreciation of foreign currency to unhedged borrowers. In context of *The DFI*, the interest rates affecting NPLs stem from repricing risk, yield curve risk, basis risk, and optionality *(The DFI*, 2016*)*. Earning and economic value approaches are used to measure the sensitivity of interest rates shocks. According to *The DFI* (2018), any unhedged positions affect *The DFI* equity earnings due to adverse changes in exchange rates resulting from exposure to

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investments outside the borders of South Africa or through its trade finance book (*The DFI*, 2019).

Wood and Skinner (2018) found inflation to be an ambiguous predictor of NPLs. Higher inflation augments the loan serviceability by borrowers, due to a reduction of outstanding debt in real terms. However, financial institutions compensate for their possible losses caused by high inflation, by demanding higher interest rates which, in turn, lessen a borrower's ability to service the debt.

Alandejani and Asutayi (2017) employed a dynamic panel approach or Gaussian Mixture Model (GMM) models to examine the bank-level and country-level factors determining Non-Performing Loans (NPLs) in the commercial banking industry of Gulf Cooperation Council (GCC) countries. The study findings revealed that the real GDP growth had a negative impact on NPLs. In terms of bank-specific factors, Risk-Weighted Assets (RWA) provide an early warning for increasing NPLs, as these reflect the high-level risk of loans portfolio combination.

From the macroeconomic / structural factors unemployment had a strong negative association with NPLs, indicating that with a rise in unemployment due to a decline in GDP, banks become risk-averse or reluctant to give loans to reduce exposure to NPLs (Kumar et al., 2018).

Haniifah (2015) employed a multiple linear regression model to investigate the effect of four macroeconomic factors, namely, the inflation rate, exchange rate, interest rate and GDP growth, on NPLs of Ugandan commercial banks. The findings revealed that inflation rate, interest rate and GDP growth have a negative, but statistically insignificant effect, on NPLs while the effect of the interest rate on NPLs is positive but insignificant.

Wood and Skinner (2018) used a multiple regression model to research the bank-specific and macroeconomic determinants of non-performing loans of commercial banks in Barbados in the period 1991 to 2015. The empirical results showed that the bank-specific factors (ROE, ROA, CAR, and loan to deposit ratio) are significant determinants of non-performing loans, while the macroeconomic variables exerting a significant influence are GDP growth, unemployment, and interest rate.

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Asfaw et al. (2016) examined major factors affecting NPLs of the Development Bank of Ethiopia, Central Region. The research encompassed both bank- and customer-specific factors. The findings of the bank-specific factors revealed that the credit assessment of the region is the major cause of NPLs. In addition, aggressive lending by the bank, compromised integrity in approval, high interest rate, poorly negotiated credit terms, and an elongated process of loan approval, were bank-specific causes for the occurrence of NPLs.

Mpofu and Nikolaidou (2018) researched 22 African countries in the Sub-Saharan region to determine the influence of macroeconomic determinants on credit risk as proxied by NPL ratio. The study used a dynamic panel data estimation technique to analyse data for the period 2000 to 2016. The outcome of the study showed that NPLs are reduced by an increase in the real GDP growth rate. Moreover, other factors, comprising of volatility index (VIX), inflation and openness of trade, amongst others, exhibited a significant and positive influence on the dependent variable NPLs.

Koju et al. (2018) employed static and dynamic panel data estimation techniques to analyse the influence of micro- (bank-specific) and macroeconomic factors to the dependent variable NPLs in a study that investigated commercial banks in Nepal for the period 2003 to 2015. The findings of the study presented a negative relationship between the independent variables including Capital Adequacy Ratio (CAR), inflation, and GDP growth rate to the dependent variable NPLs. In addition, a positive relationship was determined for determinants including inefficiency, size of assets, and export-to-import ratio to the dependent variable NPLs.

2.6.3 NPLs or Loan Defaults

According to Ofonyelu and Alimi (2013) loan defaults present the biggest threat against the survival of financial institutions, namely banks and DFIs. Loan defaults and NPLs have a similar connotation (Akwaa-Sekyi & Bosompra, 2016). Murthy and Mariadas (2017) define an NPL as a loan not being serviced as per loan agreement over a period of 90 days. Munangi and Sibindi (2020) reported that NPLs represent incurred costs to financial institutions which reduce profitability. Therefore, NPLs must be closely monitored as they are linked to the failure of financial institutions and economic turmoil (Munangi & Sibindi, 2020). Hoque and Hossain (2008) suggest that the occurrence of loan defaults can be either voluntary or involuntary. Irrespective of when loan defaults happen, financial institutions suffer adverse consequences.

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A credit scoring method is used in the financial sector by the Risk Management Department to predict the probability of loan defaults. This model assigns scores for potential borrowers by estimating the probability of default of their loans based on characteristic borrower and loan data (Chelagat, 2012).

Chortareas et al. (2020) mentioned that financial institutions also perform stress testing scenarios as part of credit risk management to predict events of loan default. NPLs were investigated against the macroeconomic factor of Gross Domestic Product (GDP) and the findings were a high surge of NPLs occurring during economic down-turn and vice versa.

Koju et al. (2018) highlighted poor credit policies, unskilled credit experts and high interest rates as the main bank-specific factors that resulted in high NPLs. From a macroeconomic perspective, a contraction in GDP, a high unemployment rate, a high inflation rate, and a weak monetary policy are noted as the major causes of high NPLs and a resulting unstable financial system.

2.7 CONCLUSION

This section provided a review of the literature covering the relevant theories and reviewed empirical studies underpinning the problem of NPLs and loan defaults being investigated. A vast volume of empirical evidence suggests that both macroeconomic and microeconomic (lender- and borrower-specific) factors influence loan defaults and NPLs, which in turn, affect the loan portfolio quality. Based on a review of empirical literature it is to be emphasised that the influence of both macroeconomic and microeconomic factors on NPLs has been examined using various techniques. Most studies have investigated the issue of NPLs in the context of commercial banks in different parts of the world and to this researcher's knowledge, most studies covered banks outside South Africa. From this perspective, there is an apparent gap in the literature with regards to the determinants of NPLs in the context of the DFIs, especially in the South African context. Laryea et al. (2016) mentioned that state-owned financial institutions tend to have higher NPLs compared to those of commercial banks. This can be attributed to the DFIs' developmental agenda as dictated by their mandate and hence, DFIs tend to undertake riskier projects that commercial banks have no inclination for, or for projects considered to be high risk but requiring large capital financing. Moreover, studies that have

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assessed the factors linked to the predictability of loan defaults from the DFIs' perspective are scant. Therefore, this study seeks to contribute by filling this gap of knowledge.

This study has been undertaken to examine and analyse with a view to solve a real-life problem of rising NPLs in the specific DFI, herein referred to as *The DFI.* The recommendations will be made for management, based on the study outcome on how to deal with the persisting problem of NPLs at *The DFI.*

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CHAPTER 3: RESEARCH METHODOLOGY

3.1 INTRODUCTION

In this section, the methodology used to conduct the research is discussed and includes the research approach and the research design of the study. The research design will cover the population of the study, unit of analysis, and sampling technique used. Moreover, the method of data collection will be explained, followed by details about the estimation technique used for data analysis to test the hypotheses presented in chapter one. Subsequently, the reliability and validity of this study are discussed, with the last section being the conclusion.

3.2 RESEARCH APPROACH

It is important for a researcher to select the appropriate research approach which will inform and guide the research design of the study (Collis & Hussey, 2014). This selection is made by subjecting the research question to three philosophical assumptions, namely Ontology, Epistemology, and Axiology. The three possible research approaches from which research can be conducted, comprises of a Positivism Paradigm, a Constructivism Paradigm, and a Pragmatism Paradigm. This research is within the Positivism paradigm because it is based on a singular reality (i.e. an Ontological Assumption) which seeks to reject or not to reject the null hypotheses presented in the first section of this report.

According to Collis and Hussey (2014) the observable and measurable phenomena are regarded as only knowledge for Positivists. In addition, Positivists try to maintain their independence and objective stance. Therefore, the epistemological position of this study is Positivistic since the researcher is distant from phenomena being examined. As presented in Section 1.3.2, and based on research questions, hypotheses were formulated to establish factors that are linked to the predictability of loan defaults in *The DFI* loan portfolio.

To answer these research questions, secondary quantitative data will be collected for analysis - knowledge is derived from measurable phenomena and not directly from participants. From this perspective, the researcher is distant and impartial. The methodological assumption is a deductive approach, as the study is testing formulated hypotheses based on existing theories. Based on the above, a Positivist approach is appropriate to carry out the study.

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3.3 RESEARCH DESIGN

The research design section provides a comprehensive blueprint pertaining to data collection methods and appropriate data analysis techniques used to answer specific research questions (Onyango & Olando, 2020).

3.3.1 Population

A population as defined by Collis and Hussey (2014), is group of all people or objects under consideration for statistical research purposes. The sample is drawn from the targeted population (Onyango & Olando, 2020). The population of this study is all *The DFI* Business Partners (BP) in the loan portfolio, or clients funded by *The DFI* for the period 2016 to 2021.

3.3.2 Unit of Analysis and Sampling frame

The unit of analysis is South African-based companies in various sectors who have been funded by *The DFI* for the period 2016 to 2021, and who had defaulted on their loans exceeding 90 days. The sampling frame of this research was *The DFI* SAP database from which BP / client specific data (i.e. loan portfolio data) was logged. The sampling frame has adequate financial and non-financial annual information to conduct an analysis of the study. The study used secondary data kept for internal administration and not for academic research purposes.

3.3.3 Sampling method and size

In this study a probability-based or systematic random sampling method was selected because every unit of a target population has an equal chance of being chosen. Moreover, systematic random sampling was found suitable due to its simplicity when dealing with a large population size, which can be time consuming. This sampling method would help to minimise the chance of biased samples (Wegner, 2012).

To draw the systematic random sampling, the first step is to determine the sample block by dividing a sample frame by selected sample size. This is followed by choosing the first sample unit from the first sample block. Subsequently, the sample units are chosen by selecting one unit from each sampling block at a constant interval from a previously sampled unit (Wegner, 2012). According to Collis and Hussey (2014) for a given population of 700 the sample size should be 248. Based on these guidelines and applying a systematic random sampling method

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as discussed above, the final sample of 910 loan portfolio account entries was determined. This sample (910) was used to process and analyse the data statistically to test the hypotheses.

3.4 DATA COLLECTION PROCESS

3.4.1 Ethical clearance

Before data is collected, ethical clearance must be obtained from the University of Cape Town Graduate School of Business. Furthermore, *The DFI* will have to grant permission for the strictly confidential use of collected data and be assured that no BP name would be revealed, including any usage of information that might compromise *The DFI* or its clients.

3.4.2 Collection of data

The secondary data will be collected on *The DFI* SAP database system and populated on an Excel spreadsheet for filtering, analysis and further processing. The client SAP database contains financial and non-financial information of *The DFI*-funded companies, as well as risk-related information. *The DFI* SAP client data base is in annual format and captures all the client's history from the time they first received funding. It is anticipated that all the information required for the study will be obtained. As this is a quantitative study, descriptive and inferential statistical analysis will be performed. The statistical software program, namely the IBM Statistical Program for Social Sciences (*SPSS*) version 28, will be used to conduct the statistical analysis required to answer research questions and test hypotheses.

3.5 EMPIRICAL MODEL

The study examines the factors that are linked to the predictability of loan defaults in *The DFI's* loan portfolio. The logistic regression technique has been adopted for analysis to examine the relationship of various predictor variables to a dichotomous dependent variable. For this study, the risk of loan defaults is examined against predictor variables, which include the type of financial instrument, credit scoring, deal complexity, firm development stage, firm industry, and firm size. In this study, the logit model is presented as follows (Antwi et al., 2012; Ochieng, 2015; Peng et al., 2002):

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$$Logit(Y) = \ln\left[\frac{\mathrm{P(Y)}}{1 - P(Y)}\right] = \beta_0 + \sum_{i=1}^{k=6} \beta_i X_i \qquad (1)$$

$where, \ln\left[\frac{\mathrm{P(Y)}}{1 - P(Y)}\right] is\ representing\ the\ log\ (odds)\ of default,$

- Y is dichotomous dependent variable (*Loan default or non-default*)
- X_i represent a set of predictor variables being investigated
- β_0 represent intercept of the model to be computed by SPSS
- β_i represent regression model coefficients for each predictor variable to be computed by SPSS

According to Boateng and Abaye (2019), the coefficients in the logistic model represent the measure of association between each predictor variable and the dependent variable. Moreover, the interpretation of logistic regression results is in the form of odds ratio (Boateng & Abaye, 2019). The coefficient (β) indicates the direction (positive or negative) between logit (Y) and predictor variable X_i (Peng et al., 2002).

3.5.1 Description of variables

3.5.1.1 Dependent variable

Loan defaults are when the borrower is in violation of the loan agreement by not making a loan payment when it is due (Addae-Korankye, 2014; Agbemava et al., 2016). In this study, the dependent variable is specific to NPLs as defined in the previous chapters. In line with the logistic model requisite for a dichotomous dependent variable, loan default is a binary dependent variable (Y_i) for this study, with dummy coding 0 and 1 denoting a dichotomous outcome as shown below:

$$Y_i = \left\{\frac{1 = \text{Loan Default } (> 90 \text{ days})}{0 = \text{Non} - \text{default } (< 90 \text{ days})}\right.$$

3.5.1.2 Independent variables

a. Type of financial instrument

The types of financial instruments are various funding products comprising of debt, equity, guarantees, and mezzanine / quasi-equity amongst others, that are used by DFIs to carry out their developmental mandate. These funding instruments are used in different ways to structure deals or transactions of different sizes, dependent on the funding need and the level of risk (Ntsaluba, 2014).

The DFIs often use concessionary types of instruments to finance various projects, such as early-stage technology start-up businesses, acquisitions, green-field or brown-field production, working capital, and trade finance (Havemann et al., 2020). From this perspective, the study investigates the influence of the coefficient financial instrument to loan defaults.

b. Credit scoring

According to Baidoo and Priestley (2016) the idea behind credit scoring is to determine the credit or loan risk based on the debtor asset market value if liability is given. The KMV-Merton model is the most popular and uses the firm's liabilities to determine the default points as well as the distance to default (Jia-ni & Yong-ping, 2015). According to Yusof and Jaffar (2012), despite being pronounced as a valuable default forecaster, the KMV model has failed to forecast defaults in certain instances due to structural model constraints. This study examines the influence and effectiveness of the credit scoring method employed by *The DFI* to mitigate loan defaults and NPLs. From this perspective, it is expected that the results of the study should reveal the lack of effectiveness in the predictability of loan defaults in the light of the persistent increase of NPLs. All applications from new and repeat clients are scored to establish the level of risk, cut-off value, after which a rejection or approval decision is made (Baidoo & Priestley, 2016). The range of Internal Risk Grading (IRG) and its interpretation is shown in Table 4.

Table 4. Credit scoring: IRG Ranges and interpretation

IRG rating	**Low Risk (≤ IRG 18)**	**Medium Risk (IRG 19 – IRG 20)**	**High Risk (≥ IRG21)**
Category 1 Clients: (Low – Medium Risk Clients)	Credit profile (IRG rating) maintained or improved – Existing clients. Performance is deemed in line with expectations Compliance with undertakings and covenants confirmed.		
Category 2 Clients:	Low – High Risk Clients capped at IRG21. Credit profile deteriorating from initial approval, particularly for existing / repeat clients. For new clients financial and non-financial information is assessed and the model outcome would place a client in any category depending on the level of risk determined.		
Category 3 Clients: (High Risk Clients)			High Risk Clients (IRG22 – IRG24) Initial amount approved to be treated as the

			defined limit. No further funding to be granted.

c. Deal complexity

According to Célérier and Vallée (2014) the development of complex products explains complexity in the financial system. However, deal complexity in the context of *The DFI* refers to the classification of a transaction as Complex or Non-complex, based on the criteria depicted in Table 5.

Table 5. Differentiation between Complex and Non-complex deal (Zikalala & Moorosi, 2011)

Non-complex transaction	**Complex transaction**
Only South African investments	Mostly outside South Africa investments
Investment size of ≤ R250 mil	Investment size of ≥ R250 mil
No syndication with other funders	Syndication transaction with other funders
No material judgements against the company or its management or directors	There are material judgements against the company or its management or directors

The implication of the deal classification in terms of Table 5 is the timelines needed to execute the transactions, i.e. 15 days for a non-complex deal from due diligence scheduling to the signing of legal agreements. This variable has been included in this study to establish the role of deal complexity relating to loan defaults. The author could not find studies that have examined this variable in the context of loan defaults and NPLs. However, it is anticipated that the effect of deal complexity will be positive on loan defaults given the time pressure exerted on dealmakers to comply with the 15-day target to finalise the non-complex deal. It must also be established whether complex deals that take longer to finalise exert an influence on loan defaults, given the inherent complexity in these transactions. *The DFI* makes investment decisions on the basis of information and Brunnermeier and Oehmke (2009) highlight the overwhelming effect of bounded rational investors when they have to process a lot of information quickly.

d. Firm development stage

Firm development stage is defined in terms of business life cycle stage, which all firms undergo over time and comprises of start-up, growth, maturity, and renewal or decline phase (Perenyi et al., 2008). The business activities of *The DFI* entails providing funding to support enterprises

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of various sizes from start-ups to small, medium, and large enterprises; to promote industrial capacity development and address market gaps in different sectors (*The DFI*, 2022). The developmental role of DFIs entails providing necessary funding for new firms to transition through different stages of entrepreneurial activity, considering they are often denied financial access by commercial banks based on asymmetry information. According to Bandyopadhyay (2006), smaller firms are more vulnerable to failure particularly in the earlier years. Therefore, the expected outcome, given the firm stages of development, means that start-ups and small to medium-sized companies (SMEs), are more likely to default. This variable has been included to examine the role which the firm development stage contributes to *The DFI* loan defaults.

e. Firm industry

As depicted in Table 2, *The DFI* through its value chain approach is at the centre of developing South Africa's important industries (Makue, 2016). The firm performance and the risk of credit default has been linked to the industry factors (Bandyopadhyay, 2006). It is in this context that this study examines this variable as a predictor of loan default in *The DFI's* loan portfolio. Agrawal and Maheshwari (2019) suggest that firms in particular industries will be more highly affected when compared to others in other industries. The adverse industry impact is hence associated with the likelihood of financial distress and a credit default. It is further noted that financial distress will have differing effects, even for firms belonging to the same industry. From the lender's point of view, the firm-specific industry plays a role in credit assessments, and therefore even viable firms can suffer the blow of the high cost of debt based on the industry in which they operate.

f. Firm size

According Hashmi et al. (2020), different proxies, including the total assets, sales revenue, employees, and market capitalisation amongst others, are used in corporate finance as a measure of firm size. Psillaki et al. (2010) highlights that large firms are highly favoured by financial institutions regarding the granting of loans and other financial instruments. This is because larger firms are deemed less likely to fail in comparison to smaller firms. Moreover, large corporations can survive economic downturns while smaller firms often struggle to raise more debt or equity particularly during adverse situations. *The DFI* has funded many firms of various sizes and the size variation in this study assesses the influence of firm size in default predictability. Most of the companies that approach DFIs for funding do so because commercial banks have rejected them or are unwilling to fund the project. Therefore, the anticipated outcome of the study is that smaller to medium companies are likely to default on *The DFI's* loans. Table 6 below shows the variables investigated for this study.

Table 6. Definitions of variables, descriptions, and sources of data

Variable	Measure	Variable Code	Data Source
Dependent variable (Y)			
Loan defaults (LD)	Nominal	Loan Default = 1	*The DFI* SAP Database
		Non-default = 0	
Independent variables (X)			
Type of financial instrument (TFI): X_1	Nominal	General Loan (33A) = 1	*The DFI* SAP Database
		Trade Finance (33I) = 2	
		Shareholder Loan (33G) = 3	
		Quasi Equity (33F) = 4	
Credit scoring (CS): X_2	Numerical	Low Risk Clients (≤ IRG 18)	*The DFI* SAP Database
		Medium Risk Clients (IRG 19 – IRG 20)	
		High Risk Clients (≥ IRG21)	
Deal complexity (DC): X_3	Nominal	Complex = 1	*The DFI* SAP Database
		Non-complex = 0	
Firm development stage (DS): X_4	Ordinal	Start-up = 1	*The DFI* SAP Database
		Growth = 2	
		Mature =3	
Firm industry (FI): X_5	Nominal	Basic metals & Mining = 1 Automotive = 2 Agro - processing = 3 Chemicals & Pharmaceutical = 4 Tourism, ITC and Media = 5 Industrial infrastructure = 6 New industries = 7 Other manufacturing industries = 8 including Heavy	*The DFI* SAP Database
Firm size (FS): X_6	Ordinal	Based on Annual Turnover: Small: ≤ R50 mil = 1 Medium: ≤ R170 mil = 2 Large: ≥ R 170 mil = 3	*The DFI* SAP Database

3.6 ESTIMATION APPROACH

According to Benthem (2017) quantitative research analysis can be performed using one of three approaches, namely, cross-sectional data, panel data, and time series. This study follows the time series approach and covers the period from 2016 to 2021. Given the objectives of the study and type of data being analysed, the appropriate choice of statistical modelling technique,

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namely logistic regression, as discussed above, was made. The logistic regression model measures the association between categorical or continuous predictor variables and dichotomous dependent variable by calculating probabilities using the Maximum Likelihood (ML) technique (Febrianti et al., 2021). By using ML function and computation of the first and second derivatives, the logistic model is able to determine parameters with the greatest probability of observed data, and hence produce the best fitting model for the data (Czepiel, 2012).

The choice of binary logistic model is due to the data structure used to analyse and predict an outcome variable (i.e. default or non-default) that is categorical including the proposed covariates. According to (Agbemava et al., 2016) when dealing with categorical data the assumption of linearity in a standard regression model is violated. However, logistic regression technique uses logarithmic (logit) transformation to model nonlinear correlation in a linear fashion. Essentially, the logit is the natural logarithm (ln) of *odds* of Y, and the *odds* are probability (π) ratios of a dichotomous dependent variable Y occurring (Ochieng, 2015). Moreover, basic assumptions of logistic regression include that an independent variable does not have to be normally distributed, or linearly related, nor interval. This means that there is no assumption of linear relationship by the model between the dependent and predictor variables (Ochieng, 2015). In simplistic form, the logistic regression model is expressed as follows:

$$Logit(Y) = natural \log(odds) = \ln\left[\frac{\pi}{1-\pi}\right] = \alpha + \beta X \qquad (2)$$

According to Peng et al. (2002) the probability (π) of occurrence of the outcome of interest (Y) is determined by applying the antilog in both sides of equation (1) as follows:

$$\pi = Probability(Y = outcome\ of\ interest \mid X = x, a\ specific\ value\ of X)$$
$$= \frac{e^{\alpha+\beta X}}{1+e^{\alpha+\beta X}} \qquad (3)$$

where π denotes the likelihood of the outcome, α represents the Y intercept, β denotes the coefficient, and e = 2.71828, a base of the system of natural logarithms (Peng et al., 2002). Given the equation (2) and (3), the model can be extended to multiple predictors as illustrated in equation (4) and (5).

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$$Logit\ (Y) = \ln\left[\frac{\pi}{1-\pi}\right] = \alpha + \beta_1X_1 + \beta_2X_2\ \beta_3X_3 \ldots. + \beta_nX_n \qquad (4)$$

where the odds of the event occurring is expressed by π, α denotes the Y intercept and coefficients are represented by βs. Moreover, in equation (4) the Xs represent the predictor variables in the model (Peng et al., 2002). The α and β is estimated using ML method instead of weighted least squares approach. According to (Ochieng, 2015) ML helps to find the best values for the model based on what is known about predictor variables. According to Peng et al. (2002) the probability (π) of the outcome of interest (Y) is expanded as follows:

$$\pi = Probability\ (Y = outcome\ of\ interest \mid X_1 = x_1, X_2 = x_2, X_3 = x_3)$$
$$= \frac{e^{\alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3}}{1 + e^{\alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3}} \qquad (5)$$

In equation (4) and (5), predictor variables denoted by Xs can be categorical or continuous. However, the dependent variable Y can only be categorical in a logistic model. Based on equation (4), the logit (Y) and Xs have a linear relationship, but the relationship of these variables is nonlinear in equation (5). Therefore, ensuring a linear relationship between these variables (*Y and X*) is achieved through natural log transformation of the *odds* in Equation (4). The direction - positive or negative - and the strength of the relationship is determined by the coefficients (β) (Peng et al., 2002). Lastly, based on the predictive approach of the study, the causality inference aspect is eliminated.

3.7 RELIABILITY AND VALIDITY

According to Collis and Hussey (2014) reliability in quantitative-based research indicates repeatability of accuracy and precision of the measurement. This is significant in cases where a research instrument was constructed to collect primary data from the respondents. The validity of the research is another measure of importance, and is concerned with the accuracy of the study findings (Collis & Hussey, 2014).

From the perspective of this study which used secondary data, the quality and trustworthiness of the collected information is reliant on the legitimacy of the data source. According to Letho (2019), verification of author or source reputation, coupled with assessing the location from which data was obtained, and the period over which data has been collected, is adequate to consider secondary data as reliable and valid. *The DFI* on which this study is conducted is highly

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reputable and based on asset size, is one of the prominent development finance institutions in South Africa. As a registered financial institution, its business conduct must comply with the Financial Sector Conduct Authority (FSCA) regulations and Financial Intelligence Centre Act 38 of 2001. Moreover, *The DFI* has excellent IT systems, including a SAP database from which client data is recorded by a records department from the time when an application is received until a loan is granted or credit approved. The recorded data on the system is kept updated and used for internal purposes. For these reasons, the collected data is deemed to be reliable and represent a true picture to prove the hypotheses.

3.8 CONCLUSION

In this chapter, the methodology of the study covering the research approach and research design, was explained. By subjecting the research question to the three philosophical assumptions, namely Ontology, Epistemology, and Axiology, it was determined that the study is quantitative. Moreover, population of the study was discussed, including the chosen method of sampling. Further discussions in the chapter covered data collection sources and the empirical model (i.e. logistic regression technique) selected to perform the analysis. The next chapter will present and discuss the findings of this study.

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CHAPTER 4: RESULTS AND DISCUSSION

4.1 INTRODUCTION

As discussed in the preceding chapters, this study examines various factors that are linked to the predictability of loan defaults in *The DFI* loan portfolio. In this chapter, research findings are presented and discussed in the sections to follow. Firstly, the descriptive statistics results for all study variables are presented followed by inferential statistics results achieved through the logistic regression technique – all presented and discussed in detail. The statistical software SPSS 28 was used to process the descriptive and inferential statistics data for all the study variables as presented in Table 6.

4.2 DESCRIPTIVE STATISTICS

Table 7 presents the loan default rates of the sample data for the period of the study, namely 2016 to 2021. Based on the sampled loan portfolio data represented by 910 account entries in total, the highest rate of defaults prior to the Covid-19 period is 94% in 2018. The loan default rates in the subsequent years are 67% which occurred in year 2016 and 2021, 63% in 2017, and 54% in 2019. The period 2020 and 2021, i.e. the Covid-19 period, exhibits the default rates of 59% and 67% respectively. This could be attributed to limited account entries in those years. As seen from Table 7, the overall loan default ratio is 67% for the study period of six years based on the sample data of 910 loan portfolio accounts entries. One can deduce from the sampled data that most default rates were experienced prior Covid-19 period, hence eliminating the anomaly of the Covid-19 pandemic period in which most businesses struggled to operate due to lockdown restrictions. As a result, abnormally high rates of loan defaults would be anticipated.

Table 7. Loan Defaults rate (%) on sampled data for period 2016 to 2021

	Loan Defaults				**Total**	
	Non-default		**Loan Default**			
	N	%	N	%	N	%
KEYDATE						
2016	180	33%	370	67%	550	60%
2017	51	37%	87	63%	138	15%
2018	5	6%	84	94%	89	10%
2019	51	46%	59	54%	110	12%
2020	7	41%	10	59%	17	2%
2021	**2**	33%	**4**	67%	**6**	**1%**
TOTAL	**296**	33%	**614**	67%	**910**	100%

Source: Candidate’s estimate from research data

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Table 8 shows that the biggest contributor to the high loan default ratio as discussed above were investments made to small firms with a turnover of less than R50 million, as they accounted for 67,3% of the total loan defaults, followed by the medium-size firms with 26,7%. This outcome is not surprising as small- (including start-ups) to medium-size firms tend to be more vulnerable and riskier to invest in due to a variety of reasons. These include poor market penetration, high market concentration risk, less product diversification, and poor management, to mention a few. All these factors are likely to result in unsustainable revenues and high defaults.

Moreover, Table 8 shows that the loan defaults of large firms are insignificant at 6% in comparison to small- and medium-size firms. This suggests that large firms tend to fail less in terms of servicing the debt as they are better managed and more diversified. Moreover, large firms are less vulnerable to economic downturns as compared to small- and medium-size firms which might struggle to raise equity in adverse economic situations.

Table 8. Firm size and loan defaults

	Loan Defaults				Total	
	Non-default		Loan Default			
	N	%	N	%	N	%
Small: ≤ R50 mil	210	70.9%	413	67.3%	623	68.5%
Medium: ≤ R170 mil	56	18.9%	164	26.7%	220	24.2%
Large: ≥ R 170 mil	30	10.1%	37	6.0%	67	7.4%
Total	**296**	**100%**	**614**	**100%**	**910**	**100%**

Source: Candidate's estimate from research data

The DFI's role includes supporting start-up businesses and medium-size firms whose business case demonstrates economic merit and the ability to service loan repayments. Frequently, early start-ups and medium-sized firms in specific industries are turned away by commercial banks for various reasons. These include not meeting the 5C's evaluation criterion to qualify for receiving a bank loan. Table 9 is in line with what has been alluded to above, since it shows that 56% of the start-ups were in default, followed by the firms in a growth phase with 31% of the defaults. The firms in a mature development stage exhibit the lowest loan defaults (13%) in the study period.

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Table 9. Development stage and Loan Defaults

	Loan Defaults				Total	
	Non-default		Loan Default			
	N	%	N	%	N	%
Start-up	187	63%	347	56%	533	59%
Growth	80	27%	188	31%	268	29%
Mature	29	10%	79	13%	108	12%
Total	**296**	100%	**614**	100%	**910**	100%

Source: Candidate's estimate from research data

The outcome in Table 8 and 9 suggests that the probability of default decreases with the size of the firm, which correlates to its development stage. Table 10 presented below shows that from the sampled loan portfolio data of 910 accounts, entries of the BPs whose loans were approved during the study period of 2016 to 2021, 75% of the loan defaults resulted from the non-complex transactions that were executed within a shorter period of 15 days, while 25% of the approved deals were classified as complex transactions.

Table 10. Deal complexity and Loan Defaults

	Loan Defaults				Total	
	Non-default		Loan Default			
	N	%	N	%	N	%
Non-complex	183	62%	460	75%	643	71%
Complex	113	38%	154	25%	267	29%
Total	**296**	100%	**614**	100%	**910**	100%

Source: Candidate's estimate from research data

To promote the country's economic development and to drive job creation, *The DFI* make investments using various funding instruments, often structured in a way that suits the needs of the firms requiring funding. Table 11 depicts observations made based on the sampled loan portfolio data for the predictor variable type of financial instrument paired with loan defaults. From the data presented in Table 7, which showed that loan defaults were 67% during the period of the study, it can be observed in Table 11 that loan defaults resulting from the term loan or general loan are prevalent at 64%. Moreover, investments made using a trade finance instrument were the second contributor to loan defaults with 17%, followed by quasi-equity (10%) and shareholder loan (9%).

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Table 11. Type of financial instrument and Loan Defaults

	Loan Defaults				Total	
	Non-default		Loan Default			
	N	%	N	%	N	%
General Loan	196	66%	392	64%	588	65%
Trade Finance	48	16%	106	17%	154	17%
Shareholder Loan	10	3%	55	9%	65	7%
Quasi Equity	42	14%	61	10%	103	11%
Total	**296**	100%	**614**	100%	**910**	100%

Source: Candidate's estimate from research data

To differentiate the good borrowers from the bad ones, *The DFI* make use of credit scores as a risk measure of a client's probability of default. From the sample of the study, Table 12 shows that majority represented by 60% of the clients that were deemed to be low risk at the time of credit approval, 63% of the loans defaulted versus 53% which did not default. Moreover, as observed in Table 12, of the 32% of the clients categorised as high-risk at the time of approval, 30% of the loans granted ended up in default. The medium-risk clients which accounted for 9% of the total contributed the least to loan defaults – a mere 7% during this period.

Table 12. Credit scoring and Loan Defaults

Credit scoring	Loan status				Total	
	Non-default		Loan Default			
	N	%	N	%	N	%
Low Risk Clients (≤ IRG 18)	158	53%	384	63%	542	60%
Medium Risk Clients (IRG 19 – IRG 20)	34	11%	46	7%	80	9%
High Risk Clients (≥ IRG21)	104	35%	184	30%	288	32%
Total	**296**	100%	**614**	100%	**910**	100%

Source: Candidate's estimate from research data

Table 13 shows the firm industry and loan defaults and, based on the sampled data most (41%) of loan defaults resulted from the Tourism, ITC and Media industry, followed by New Industries with 20%. Other industries like Industrial Infrastructure, and Agro-processing, are almost equally distributed with a single digit loan default of 7% to 9%. Basic Metals and Mining contributed the least (2%) to the loan defaults.

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Table 13. Firm industry and Loan Defaults

	Loan Defaults				Total	
	Non-default		Loan Default			
Basic metals & Mining	9	3%	14	2%	23	3%
Automotive & Transport Equipment	12	4%	27	4%	39	4%
Agro - Processing	25	8%	43	7%	68	7%
Chemicals & Pharmaceutical	22	7%	55	9%	77	8%
Tourism, ITC and Media	60	20%	252	41%	312	34%
Industrial infrastructure	18	6%	47	8%	65	7%
New industries	125	42%	123	20%	248	27%
Other manufacturing industries	25	8%	53	9%	78	9%
Total	**296**	100%	**614**	100%	**910**	100%

Source: Candidate's estimate from research data

4.3 CORRELATION RESULTS

Table 14 presents the Pearson correlation results for the predictor variables of this study. The correlation analysis coefficient is denoted by *r*, which is a measure of strength and provides direction – either Negative or Positive - of the linear relationship between the two numeric variables. The strength of linear association ranges between -1 and +1, where -1 indicates a perfect negative correlation, and +1 indicates a perfect positive correlation, and 0 indicates no correlation at all (Wegner, 2012). The correlation analysis has been performed using the SPSS to determine if there is multicollinearity between the predictor variables, which can result in unreliable estimates.

Table 14. Pearson correlation analysis

Correlations						
	Firm industry	Firm size	Type of financial instrument	Deal complexity	Credit scoring	Development stage
Firm industry	1					
Firm size	$-.171^{**}$	1				
Type of financial instrument	$.106^{**}$	0,008	1			
Deal complexity	-0,060	0,002	$-.123^{**}$	1		
Credit scoring	0,032	-0,001	-0,029	0,059	1	
Development Stage	-0,018	$.141^{**}$	0,040	0,045	$-.079^{*}$	1

Note: *. Correlation is significant at the 0.05 level (2-tailed); **. Correlation is significant at the 0.01 level (2-tailed). Source: Candidate's estimate from research data

The correlation results in Table 14 show no major connection between the predictor variables of the study. None of the correlation coefficients in the results presented in Table 14 show a

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medium to very high association between the predictor variables. Low negative correlation exists between firm size and firm industry, given the correlation coefficient (*r*) of -1,71. Firm size and development stage exhibit low positive correlation with *r* of 0,141. Type of financial instrument and firm industry shows low positive correlation since *r* is 0,106. Lastly, Type of financial instrument and deal complexity also show low negative correlation with a coefficient (*r*) of -0,123. These findings indicate that no multicollinearity exists between the predictor variables. Therefore, all the predictor variables are fit to be included in the regression analysis.

4.4 EMPERICAL RESULTS

This section discusses the empirical findings of the study in line with the six hypotheses presented in chapter one. The testing of the hypotheses was performed through IBM SPSS 28 and the analytical technique employed is the binary logistic regression, Logit Model. This model is used when the dependent response variable is binary in nature. It predicts the probability of the dependent response; in this case the dependent variable is the loan defaults coded as 1 for loan default and 0 if not defaulted. The dependent variable was examined at 95% confidence interval against various predictor variables (numerical and categorical), as presented in Table 6 in the preceding chapter. The results presented in this section encompass the following:

- ❖ The overall model evaluation
- ❖ The model goodness of fit
- ❖ The statistical test and assessment of the predicted probabilities

a) Overall model evaluation

According to Peng et al. (2002) a better fit to the data for the logistic regression model is realized when there is an improvement to the Block 0 or Null Model, which comprises of the intercept only without any independent variables used in the model. Table 15 below depicts the Null Model of the study. In general, this model is not very informative, apart from its use as a baseline in comparison to the model containing all the predictor variables. For this study, the Null Model shows 67,5 per cent and this is how well the model predicts the outcome variable in the absence of the predictor or independent variables. Consequently, all observations would be predicted to fit into the largest outcome category.

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Table 15. The Block 0 (Null Model)

Classification Tablea,b					
Observed			**Predicted**		
			Loan Defaults		Percentage Correct
			Non-default	Loan Default	
Step 0	**Loan Defaults**	Non-default	0	296	0,0
		Loan Default	0	614	100,0
	Overall Percentage				67,5
a. Constant is included in the model.					
b. The cut value is ,500					

Source: Candidate's estimate from research data

b) The model goodness of fit statistics

Table 16 shows the output of the omnibus test of model coefficients which is used to test the model fit, or to determine if the model adequately describes the data. In this case, the model shows significant results ($p < 0.05$) which indicate a good model fit. This shows that there is a significant improvement in model fit when the logistic model includes predictor variables in comparison to the null model.

Table 16. Omnibus Test of the Model Coefficient

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	155,496	18	0,000
	Block	155,496	18	0,000
	Model	155,496	18	0,000

Source: Candidate's estimate from research data

Another test that is undertaken to evaluate the model fit is the Hosmer and Lemeshow (*H–L*) test presented in the output shown in Table 17 below.

Table 17. Hosmer and Lemeshow Test

Hosmer and Lemeshow Test			
	Chi-square	df	Sig.
Step 1	7,854	8	0,448

Source: Candidate's estimate from research data

The Hosmer and Lemeshow test indicates a poor fit when the p-value is less than 0.05. Table 17 exhibit that H-L test produced statistically insignificant results of 0,448 ($p > 0.05$), confirming that the model fits the data very well.

The model summary presented in Table 18 provides the Pseudo R^2, which does not technically explain the variation in the dependent variable exactly the same as in Ordinary Least Squares regression (OLS) model. This postulates that the Pseudo R^2 denotes an approximate variation that can be explained by predictor variables in the model in respect of the dependent variable.

Table 18. Model Summary

Model Summary			
	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Step 1	992.527a	0,157	0,219

Source: Candidate's estimate from research data

Table 18 shows two R^2 indices, namely Cox and Snell and Nagelkerke. The Nagelkerke R^2 is normally used to explain the variation as it is the adjusted version of Cox and Snell R^2. In this case the model summary indicates that 21,9% of the total variation in the dependent variable (i.e. Loan Defaults) is accounted for by the variation in the six predictor variables.

c) The statistical test and assessment of the predicted probabilities

The predictive accuracy of the logistic model is evaluated and presented in Table 19 below. The Classification Table provides an indication of how well, i.e. the predictive accuracy, the model predicts the correct category, namely loan defaults or non-defaults, when predictor variables are included. The results of Table 19 are compared to the Null Model (*Block 0*) Classification table presented in Table 15, to determine if there is an improvement on the Null Model results.

Table 19. Classification Table

<table>
<tr><th colspan="6">Classification Tablea</th></tr>
<tr><th colspan="3" rowspan="3"></th><th colspan="3">Predicted</th></tr>
<tr><th colspan="2">Loan Defaults</th><th rowspan="2">Percentage Correct</th></tr>
<tr><th>Non-default</th><th>Loan Default</th></tr>
<tr><td rowspan="3">Step 1</td><td rowspan="2">Loan Defaults</td><td>Non-default</td><td>124</td><td>172</td><td>41,9</td></tr>
<tr><td>Loan Default</td><td>71</td><td>543</td><td>88,4</td></tr>
<tr><td colspan="2">Overall Percentage</td><td colspan="2"></td><td>73,3</td></tr>
<tr><td colspan="6">a. The cut value is .500</td></tr>
</table>

Source: Candidate's estimate from research data

The first raw percentage (41.9%) shows Specificity, also referred to as true negative rate, which indicates the percentage that falls into the non-target variable, i.e. non-default. In this case, the

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model correctly predicted 124 non-defaults while in the same category, 172 were incorrectly classified. The second raw percentage (88,4%) shows the Sensitivity, referred to as the true positive rate, indicating the observed cases that fall in the target group, i.e. loan defaults. Therefore, the model correctly predicted 543 to fall into the loan default group and 71 were incorrectly predicted in the same category. The overall model accuracy is 73,3%, indicating good sensitivity of the model and the appropriate classification. In comparison to the Block 0 model, there is an improvement from 67,5% to 73,3% when predictor variables are included.

Table 20 presents the output of the logistic regression model, showing the relationship between the six predictor variables and the outcome, loan defaults status. The model beta coefficients denoted by β which can be negative or positive as determined by using a maximum likelihood technique in the SPSS. Moreover, the level of statistical significance for each of the predictor variables tested using the Wald (χ^2) statistic is also given as part of the model output presented in Table 20. In the logistic model, the odds ratios are derived directly from the regression coefficients. The beta (*β*) represents the predicted change in log odds, meaning the one-unit change in the predictor variable, results in Exp (*β*) change in the probability of outcome. The results show that not all independent variables are statistically significant.

Firm size

The logistic regression model results indicates that overall, Firm size is observed to be a statistically significant predictor to *The DFI* loan defaults given the p-value of 0,006 ($p < 0.05$). Therefore, the null hypothesis (H2Co) is rejected. Since the predictor variable Firm size was multi-category, using Small Firms as the reference group. First, the coefficient of medium firms is positive but insignificant ($p > 0.05$), which suggests that the differences in default status of small and medium firms is negligible. The coefficient of the large firms as proxied by turnover is observed to be negative and statistically significant ($p < 0.05$). This indicates that the large firms are associated with lower default probability compared with small firms. Specifically, the odds of large firms defaulting on *The DFI* loans are 0,365 times less when compared to small firms' default on loans. This can be explained by diversified revenue streams, better management, high market share and capital structure of large firms, in comparison with small firms. For example, small firms often experience difficulties in raising equity or debt finance, compared to large firms which rely on the strength of their balance sheet, reputation, and access to capital markets, to name a few options. Consequently, small firms are more vulnerable to defaulting on loans, given their small size and market position,

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relative to large firms. The findings are consistent with previous studies (Pradhan & Pandey, 2018; Messai & Jouini, 2013).

Table 20. Logistic regression results

	B	S.E.	Wald	Sig.	Exp (B)
Firm size (Ref_Small (1): Turnover ≤ R50 mil)			10,259	0,006	
Medium: ≤ R170 mil (2)	0,046	0,201	0,053	0,818	1,047
Large: ≥ R 170 mil (3)	-1,009***	0,322	9,806	0,002	0,365
Deal complexity (Ref_ Non-Complex)					
Complex (1)	-0,557***	0,180	9,584	0,002	0,573
Credit scoring (Ref_Low Risk Clients: ≤ IRG 18)			24,283	0,000	
Medium Risk Clients (IRG 19 – IRG 20)	1,540***	0,331	21,711	0,000	4,666
High Risk Clients (≥ IRG21)	-0,132	0,468	0,080	0,778	0,876
Period (Years) _ (Ref_Pre-Covid-19)					
Post-Covid-19 (2020-2021)	-0,438	1,010	0,188	0,665	0,645
Type of financial instrument (Ref_General Loan)			26,430	0,000	
Trade Finance (2)	-0,055	0,256	0,047	0,829	0,946
Shareholder Loan (3)	0,126	0,237	0,283	0,595	1,134
Quasi-equity (4)	1,850***	0,371	24,861	0,000	6,362
Firm industry (Ref_ Basic Metals & Mining**)**			88,198	0,000	
Automotive (2)	0,398	0,470	0,716	0,398	1,488
Agro-processing (3)	-0,466	0,377	1,525	0,217	0,628
Chemicals & Pharmaceutical (4)	0,186	0,381	0,238	0,625	1,204
Tourism, ITC and Media (5)	1,552***	0,378	16,845	0,000	4,722
Industrial infrastructure (6)	0,100	0,391	0,066	0,798	1,105
New industries (7)	-1,290***	0,308	17,479	0,000	0,275
Other manufacturing industries (8)	-0,086	0,621	0,019	0,890	0,918
Development stage (Ref_Start-up)			0,791	0,673	
Growth (2)	-0,171	0,306	0,314	0,575	0,843
Mature (3)	-0,247	0,291	0,723	0,395	0,781
Constant	0,173	1,133	0,023	0,879	1,189

Note: ****Significance at the 1% level.* Source: Candidate's estimate from research data

Deal Complexity

The results shows that the predictor variable deal complexity is statistically significant in predicting loan defaults of *The DFI* given the p-value of 0,002 ($p < 0.001$). Therefore, the null hypothesis (H1Co) is rejected. Since this was a multi-categorical variable, Non-complex deals are used as a reference category. The coefficient of the Complex deals is negative and statistically significant ($p < 0.05$) concerning loan default predictability in comparison to Non-complex transactions. This postulates that Complex transactions have a lower default

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likelihood on *The DFI* loans in comparison with Non-complex transactions. This is evident from the results, as the odds of defaulting on *The DFI* loans are reduced by 0,573 times for Complex transactions in comparison to Non-complex transactions. To the best of this researcher's knowledge, no studies could be found in relation to loan defaults and Deal complexity to which these findings could be compared. This could be attributed to the fact that Deal complexity is not a standard financial metric and could be defined differently by various financial institutions.

Credit scoring

The results shows that credit scoring is statistically significant in predicting loan defaults of *The DFI* given the p-value of 0,000 ($p < 0.05$). Therefore, the null hypothesis (H1Bo) is rejected. Similarly, as this variable is multi-categorical, the low-risk client (≤ *IRG 18*) category is used as a reference group. Firstly, the coefficient of medium-risk clients (*IRG 19 – IRG 20*) is observed to be positive and statistically significant ($p < 0.05$) when compared with a reference group category, suggesting that medium-risk clients have higher probability of default on *The DFI* loans as compared to low-risk clients. Specifically, odds of defaults are 4,666 times higher for medium risk clients relative to low-risk clients. This is an expected finding in line with the risk management grading procedure of *The DFI* which validates the default prediction model currently in use. This is based on the higher credit risk ranking given to medium-risk clients relative to those assessed as low risk, i.e. baseline category. In contrast, the coefficient for high-risk clients (≥ *IRG21*) is negative and statistically insignificant ($p > 0.05$) for predicting defaults on *The DFI* loans when compared to low-risk clients. Therefore, the results of this study on predictor variable credit scoring are consistent with the findings of Yusof and Jaffar (2012).

Type of financial instrument

The coefficient financial instrument is a significant predictor of loan defaults in *The DFI* loan portfolio based on the p-value of 0,000 ($p < 0.05$). Therefore, the null hypothesis (H1Ao) is rejected. Since this variable is multi-categorical, general loans are used as reference group category. The results exhibit that the quasi-equity instrument coefficient is positive and statistically significant ($p < 0.05$) when compared to the general loan instrument. From these findings, one can deduce that the quasi-equity instrument has a higher likelihood of default on *The DFI* loans as compared to a general loan facility. Specifically, the odds of default are 6,362 times higher for investments made using a quasi-equity instrument in comparison to a general

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loan facility. This suggests that the quasi-equity instrument has a higher default risk than general loan or senior debt instrument. Moreover, in a default event, a risk of loss is much higher in a quasi-equity than a general loan because capital and interest repayments are subordinated. The same effect is also reported for shareholder loan instruments, although the estimated coefficient is insignificant. In contrast, Trade Finance instruments are observed to be associated with a lower probability of default, compared with general loans, although the coefficient is statistically insignificant ($p > 0.10$). The findings in this study are consistent with the studies of Chelagat (2012) and Agbemava et al. (2016) that concluded that different types of loan facilities have a variable influence on loan defaults or NPLs, depending on their weighting. It should be noted that, depending on the deal structure, each approved transaction can have a combination of financing instruments under one transaction.

Firm industry

The firm industry variable is statistically significant for predicting loan defaults of *The DFI* based on the p-value of 0,000 ($p <0.001$), which is why the null hypothesis (H2Bo) is rejected. The coefficient of the New Industries (7) is negative and statistically significant ($p <0.001$) for predicting defaults of *The DFI* loans in comparison to Basic Metals & Mining (reference group category). This suggests that firms classified under New Industries are associated with a lower probability of default when compared with Basic Metals & Mining firms. Specifically, the odds of defaulting on *The DFI* loans decreases by 0,275 times if a firm belongs to New Industries, as compared with Metals and Mining firms. This suggests that firms in the New Industries value chain have a lower likelihood of defaulting on *The DFI* loans compared to firms in the Basic Metals & Mining industry. In contrast, the coefficient of the Tourism, ITC and Media industry is observed to be positive and statistically significant ($p <0.05$), meaning that firms in this sector have higher likelihood of defaulting when compared to those belonging to the Basic Metals & Mining industry. In particular, the odds of default on *The DFI* loans are 4,722 times higher for firms in the Tourism, ITC and Media industry when contrasted with firms belonging to the Basic Metals and Mining sector. However, the results show that industries such as the Automotive, Agro-processing, Chemicals & Pharmaceutical, Industrial Infrastructure, and a number of other manufacturing industries are at an individual level statistically insignificant ($p >0.05$) regarding the prediction of defaults of *The DFI* loans when compared to Basic Metals & Mining. Therefore, the findings in this study are in line with the expected outcome for this predictor variable, and are consistent with findings by Agrawal and Maheshwari (2019) and Bandyopadhyay (2006).

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Firm Development Stage: Start-up / Growth / Matured

The coefficient of the Firm Development Stage is not a statistically significant predictor of defaults on *The DFI* loans, based on the p-value of 0,673 ($p > 0.05$). Since this was a multi-categorical variable, the results were insignificant ($p > 0.05$) for individual variables relating to those in a Growth and Matured stage, when compared to the Start-up reference group category. Therefore, the null hypothesis (H2Ao) is not rejected. In can be concluded that there is no link between firm development stage in terms of business life cycle and probability of default on *The DFI* loans. The findings contradict the expected results, as cited from the study of Bandyopadhyay (2006).

Lastly, the period in years (Pre- or Post-COVID-19) included in the analysis showed no statistical significance ($p > 0.05$) to the model concerning the prediction of loan defaults of *The DFI*.

From the above discussion of the results, it can be concluded that five predictor variables of this study, namely Firm industry, Firm size, Deal complexity, Credit scoring, and Type of financial instrument, are linked to predicting defaults in *The DFI's* loan portfolio. Further discussion on these findings and their implications will be covered in the next chapter.

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CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 INTRODUCTION

As presented in the first chapter, the investigated variables of the study against the dependent variable loan defaults, were divided into client and loan-characteristic factors. In this final chapter, the main findings are summarised and discussed, and the conclusions are drawn from empirical findings presented in the preceding chapter. This is followed by policy recommendations, as the study has implications for management of *The DFI*. Lastly, delimitations in the study are highlighted, followed by fields for future research.

5.2 SUMMARY AND CONCLUSION

The study was undertaken to investigate factors that are linked to the predictability of loan defaults in *The DFI* loan portfolio. This was spurred by an interest in the consistent rise in *The DFI's* non-performing loans as normally reported in the corporation's annual integrated reports. For this reason, a logistic regression technique was employed for empirical analysis in order to test the hypotheses and determine the predictability of a dichotomous dependent variable, i.e. loan defaults, against six predictor variables including type of financial instrument, credit scoring, deal complexity, firm development stage, firm industry, and firm size.

Based on the research questions presented in Chapter One, the following paragraphs elaborate on the study findings as presented in the preceding chapter:

The firm industry was found to be a statistically significant predictor of defaults in *The DFI* loan portfolio. It may be concluded from the study findings that different industries are impacted differently by adverse economic conditions, i.e., business cycles, including other industry-specific factors that may affect firm's profitability and ability to service debt obligation. Therefore, in support of Murthy and Mariadas (2017), the probability of defaults will not be the same across industries as indicated by the findings of this study. The firms belonging to New Industries were statistically significant in predicting defaults of *The DFI* loans compared to Basic Metals & Mining. Given the fact that *The DFI* is industry-focussed, the findings suggest continued support for firms in New Industries. Currently, support for this sector is in alignment with the government development drive in priority sectors including

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renewable energy technologies, in the light of the existing challenges in the power generation sector of South Africa. However, the Tourism, ITC and Media industry were found to be more prone to an increase of loan defaults in *The DFI* loan portfolio. As the study is unable to identify which sub-sector in this value chain, i.e. Tourism, ITC, or Media, is the biggest contributor to loan defaults, it is not easy to draw proper conclusions. However, since tourism often thrives on the back of information technology, proper due diligence is crucial when dealing with high-tech enterprises, as they are often characterised by large capital investment and high credit risk when compared to other industries. One of the market failures *The DFI* is set to alleviate concerns its effort to increase the financing channels of high-tech enterprises, because commercial banks are reluctant to support these given the high risk of unproven technology and the business model.

The study findings on Firm size as proxied by turnover was statistically significant, indicating that this variable has an influence on default predictability of *The DFI* loans. It can be concluded from the study findings that large firms are less susceptible to defaulting on *The DFI* loans as opposed to small firms. These findings might imply that a reduction of loan defaults or NPLs is possible when *The DFI* extend financing primarily to large firms, as these exhibit less proclivity to defaulting when contrasted with small firms. But this is not realistic since the role of *The DFI* is to address market failures, such financial exclusion due to asymmetric information and credit rationing amongst other factors, that affect small to medium firms. Moreover, other market failures which DFIs aim to address is the collateral requirement by commercial banks. Generally, most start-up businesses or SMEs are excluded financially due to among other factors, a lack of collateral - see the 5Cs of credit assessment criterion. However, if the business exhibits economic merit, *The DFI* chooses to obtain security if it is available and does not reject an applicant due to a lack of collateral. This makes *The DFI* a lender of last resort, particularly in strategic priority sectors and infant industries which could be deemed high risk for commercial banks.

The study found that deal complexity has an influence in predicting defaults of *The DFI* loans. The results for this predictor variable cannot be compared to any previous studies since none was found to have examined this variable in the context of loan defaults and NPLs. This might be attributed to the fact that deal complexity is not a standard financial metric used across various financial institutions. Moreover, deal complexity can have different descriptions or criteria unlike the one presented for *The DFI*. Nonetheless, results showed that non-complex

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deals have more propensity to loan defaults, as compared to complex transactions. This suggests that quicker turnaround times could result in loan defaults given a little time to process all the information for credit approvals. *The DFI's* investments are generally made based on the quality of information. However, often the information presented for funding applications lacks in quality, which invariably creates a bottleneck in the procedure to process it swiftly. This might introduce errors when dealing with high numbers of non-complex transactions. However, the reasons for non-complex deals to be more prone to defaults as compared with complex deals, could also be attributable to unknown factors, since the logistic model cannot determine causality.

The outcome of the study found credit scoring to be statistically significant in predicting loan defaults. It can be concluded that without a credit scoring mechanism, loan defaults would be uncontrollable higher in *The DFI* loan portfolio. Moreover, credit scoring not only assists with quantifying and rationalising the credit risks of applicants, but also ensures that lenders are rewarded accordingly in line with the risk taken. This means even though *The DFI* is not profit-driven, it must still be profitable to remain sustainable, particularly as a self-funded state entity which doesn't receive any grants from the government treasury. However, despite *The DFI* having advanced credit scoring software tools in place, loan defaults or NPLs are still an ongoing issue. From this perspective, this means that the evaluation of credit risk through, for example, the KMV credit scoring model cannot accurately produce perfect results or eliminate defaulters from the system. Moreover, the escalating NPLs of *The DFI* could be attributed to other unknown factors which are not covered or investigated in this study.

With regard to the development stage of the firm in terms of the business life cycle, demonstrated insignificant results regarding loan default predictability. This finding indicates that the firm's development stage is not linked to loan defaults of *The DFI* and has no influence as a predictor in the model. This independent variable was expected to have an influence in loan default predictability, because the firm's life cycle stage often determines the risk profile of clients. For example, at the start-up phase of the business life cycle, firms tend to manifest higher default rates because this stage of their development is characterised by negative operating cash flows stemming from an inconsistency in sales revenues, slow penetration of the market, low cash flows, and uncertainty in cost structure. In contrast with this, firms during the growth and mature life cycle stages, enjoy positive cash flows which means that defaulting

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on their loan obligations is unlikely due to a proven business model and a growing customer base.

The findings on the type of financial instrument were statistically significant in loan default predictability. From this perspective, the findings are in line with the studies of Chelagat (2012) and Agbemava et al. (2016) which concluded that, depending on their weighting, different types of loan facilities have a varying influence on loan defaults or NPLs. Moreover, it must be mentioned that *The DFI's* finance structuring is based on a cashflow-matching strategy, where repayment ability is linked to predictable cashflows from normal business operations. This way of structuring a deal ensures a debt servicing ability by clients to prevent defaulting on loans. Moreover, special schemes are employed to reduce the cost of debt and ensure loan servicing ability by firms in order to minimise the risk of default. A variety of funding instruments are used in any combination depending on the financing need. The results showed that quasi-equity instruments, such as a sub-ordinated loan, are more likely to increase loan defaults in *The DFI's* loan portfolio. This financing instrument, i.e. quasi-equity financing, is often used when the capital structure is below (<40%) *The DFI* financing norms. A quasi-equity instrument is a high-risk instrument as it is unsecure and based on projected cash flows linked to future firm performance. Moreover, a quasi-equity instrument is considered junior to any other bank debt, meaning *The DFI* will be last to be paid in the case of the liquidation of the borrowing firm. Despite the possibility of higher earnings in future, the use of a quasi-equity instrument in the form of a subordinated loan should be avoided and only considered under special circumstances. This is because, in the event of default, the risk of loss is substantially higher than it is for senior loans, coupled with the fact that interest and loan repayments are subordinated.

In conclusion, to answer the first research question as presented in the Chapter One, it was empirically determined in this study that credit scoring, deal complexity and type of financial instrument were all statistically significant and are linked to the predictability of loan defaults in *The DFI* loan portfolio. To answer the second research question, firm industry and firm size were statistically significant and linked to loan default predictability, while firm development stage was insignificant and not associated with credit default prediction.

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5.3 RECOMMENDATIONS

The probability of default can result from many factors, and this study demonstrated that various loan and client factors, including type of financial instrument, credit scoring, deal complexity, firm size, and firm industry, were among the significant factors linked to the predictability of loan defaults in *The DFI* loan portfolio. Based on the study findings, the following are recommendations for *The DFI* management to consider in order to reduce loan defaults or NPLs:

- ❖ Client loan portfolio monitoring is key to a reduction of loan defaults and borrowers need to adhere to the loan agreements throughout the loan term. Fostering good relationships with clients or BPs is beneficial to the reduction of loan defaults since borrowers will be compelled to be transparent about any challenges encountered by the business, and hence there will be a reluctance to default.
- ❖ Business support should be provided to SMEs free of charge, as small to medium-size firms are more prone to loan defaults than large ones.
- ❖ It is important for management to ensure that funding disbursements happen on time, as per deal classification timelines. This will ensure that there are no missed market opportunities by the clients which might cause loans to default.
- ❖ In the case of non-complex transactions, the proper due diligence process needs to be followed, while at the same time, quicker turnaround times for the approval of transactions must be ensured. Management might need to consider implementing a high-performance culture and train and equip dealmakers to be more efficient in order to deliver on transactions without compromising quality.
- ❖ *The DFI* management must ensure that proper deal structuring happens, and adequate funding is provided to meet the client's business needs, depending on the loan purpose, in order to avoid loan diversion. The correct financial instrument or a combination of these, must be used for optimum deal structuring. This should be supported by a matching cashflow principle, enabling the available special funding schemes to reduce the cost of funding. This should minimise the probability of loan default. *The DFI* should insist on a shareholder equity contribution to ensure a healthy capital structure which minimises the use of quasi-equity instruments in the deal financing composition.
- ❖ Based on the outcome of the study, the probability of default is expected on small- to medium-sized firms, especially if the firm is operating in a particular industry. Therefore, non-financial measures, such as the firm's industry, managerial competency, corporate governance, etc., must be considered as essential in credit scoring methods,

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which currently only consider standard financial ratios as key inputs to a default probability model. Incorporating qualitative information can assist in properly determining a firm's creditworthiness or default probability, which cannot be inferred exclusively from financial information.

5.4 LIMITATIONS OF THE STUDY

As previously mentioned, the aim of this study was to empirically investigate a work issue of escalating NPLs. The study has the attribute of a case study structure because only one specific DFI was investigated. Consequently, the major limitation of the study is that the findings are not able to be generalised across all South African based DFIs. The firms in *The DFI* loan portfolio could exhibit different characteristics to those funded by other DFIs in South Africa.

The other limitation of the study is the inaccessibility of certain characteristic client information on *The DFI's* SAP database. This information includes shareholders' personal information such as age, educational background, gender and corporate shareholding in firms financed by *The DFI*. This information could have helped the study gain more insight on the issue of loan defaults or NPLs. Moreover, the short period of the study (2016 to 2021) is considered a limitation to the study outcome.

Lastly, based on the sampling technique adopted for this study, which aimed at avoiding selection bias, the final sample lacked the equal distribution of account entries on each year of the study period, including even distribution per sector.

5.5 FIELDS FOR FUTURE RESEARCH

Based on the limitations of this study, future studies could investigate the issue of loan defaults or NPLs relating to other DFIs in South Africa to make the results more generally applicable. Future studies could also investigate other variables which were not explored in this study. There is room to investigate the issue of loan defaults or NPLs in South Africa by using both a quantitative and qualitative approach in order to gain a better understanding of the issue, especially from the causality perspective.

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APPENDICES

Appendix A: Approved Ethics Clearance

UNIVERSITY OF CAPE TOWN

FACULTY OF COMMERCE

Igniting Knowledge and Opportunity

Commerce Faculty Ethics in Research Application Form

Any person planning to undertake research in the Faculty of Commerce at the University of Cape Town is required to obtain ethical clearance. This form is intended for undergraduate students, honours students, PD Dip students and Masters students whose research component is less than 90 credits.

Once this form is completed it should be sent via email to your departmental ethics representative. Your supervisor will be able to provide you with the contact details.

It is assumed that the researcher has read the UCT Code for Research involving Human Subjects (Available at http://web.uct.ac.za/depts/educate/download/uctcodeforresearchinvolvinghumansubjects.pdf) in order to be able to answer the questions in this form. Students must include a copy of the completed form with the dissertation/thesis when it is submitted for examination.

1. PROJECT DETAILS			
Project title:	**Predicting Loan Defaults in Development Financing in South Africa**		
Principal Researcher/s:	Mandla Sibiya	**Email address(es):**	SBYPET003@myuct.ac.za or mandlas@idc.co.za
Research Supervisor:	Prof Latif Alhassan	**Email address(es):**	latif.alhassan@uct.ac.za
Co-researcher(s):	N/A	**Email address(es):**	
Department: MCom Development Finance (Graduate School of Business)			

Brief description of the project:

The research project has been undertaken to investigate factors that are linked to the predictability of loan defaults in the context of the Development Finance Institution (DFI) based in South Africa. To comply with the prescripts of POPIA & PAIA and to protect the organisation, the specific DFI in which the study is conducted shall be referred to as the "State Owned Entity (SOE)". The evidence suggests that NPLs are consistently increasing at the SOE as reported on annual reports. Therefore, to deal with this issue it was deemed fitting to examine the issue of loan defaults empirically with focus on loan and client characteristics predictor variables. The study contributes to fill the knowledge gap since most studies that have investigated the issue have focussed on lender specific variables and macroeconomic determinants in commercial banks based in other countries.

Data collection: (please select)

☐ Interviews ☐ Questionnaire ☐ Experiment ☒ Secondary data ☐ Observation

☐ Other (please specify): ____

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Have you attached a research proposal OR a literature review with research methodology? (please select) ☒Yes ☐No

2. PARTICIPANTS (N/A)

2.1 Does the research discriminate against participation by individuals, or differentiate between participants, on the grounds of gender, race or ethnic group, age range, religion, income, handicap, illness or any similar classification?		NO
2.2 Does the research require the participation of socially or physically vulnerable people (children, aged, disabled, etc.) or legally restricted groups?		NO
2.3 Will you be able to secure the informed consent of all participants in the research? (In the case of children, will you be able to obtain the consent of their guardians or parents?)		NO
2.4 Will any confidential data be collected or will identifiable records of individuals be kept?		NO
2.5 In reporting on this research is there any possibility that you will not be able to keep the identities of the individuals involved anonymous?		NO
2.6 Are there any foreseeable risks of physical, psychological or social harm to participants that might occur in the course of the research?		NO
2.7 Does the research include making payments or giving gifts to any participants?		NO

If you have answered **YES to any of these questions**, please describe how you plan to address these issues (append to form):

Affiliations of participants: (please select)

☐Company employees ☐Hospital employees ☐General public ☐Military staff ☐Farm workers ☐Students

☐ Other (please specify): The study will use secondary data that will be collected on the company database.

Race / Ethnicity:

Are you asking a question about race/ethnicity in your questionnaire?

☐ Yes ☒No

Which race categories have been used?

Have you included the option: "Prefer not to answer" as part of your race/ethnicity question?

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3. Provision of Services

Does your research involve the participation of or provision of services to communities?
If your answer is YES, please complete below:

3.1 Is the community expected to make decisions for, during or based on the research?		NO
3.2 At the end of the research will any economic or social process be terminated or left unsupported, or equipment or facilities used in the research be recovered from the participants or community?		NO
3.3 Will any service be provided at a level below the generally accepted standards?		NO

If you answered YES to any of these questions, please describe below how you plan to address these issues.

3. ORGANISATIONAL PERMISSION

If your research is being conducted within a specific organisation, please state how organisational permission has been/will be obtained:

Upon obtaining ethical clearance, the management / company executive will be approached to seek permission to use the company client data for research purposes. It will be indicated that no client name shall be revealed, or no use of the collected information will compromise the organisation or its clients. The formal approval letter will be requested for record.

Have you attached the letter from the organisation granting permission? (please select)

☐ Yes ☒No, but this **will be** obtained before commencing the research ☐ Not applicable

Are you making use of **UCT students** as respondents for your research? (please select) ☐ Yes ☒No

If yes, have you contacted Executive Director: Student Affairs for permission? (please select) ☐ Yes ☐No

Was approval granted? (please select) ☐ Yes ☐No ☐Awaiting a response

Are you making use of **UCT staff** as respondents for your research? (please select) ☐ Yes ☒No

If yes, have you contacted Executive Director: Human Resources for permission? (please select) ☐ Yes ☐No

Was approval granted? (please select) ☐ Yes ☐No ☐Awaiting a response

`

Contact Emails: Executive Director: Human Resources (Miriam.Hoosain@uct.ac.za)
Executive Director: Student Affairs (Moonira.Khan@uct.ac.za)

4. INFORMED CONSENT

What type of consent will be obtained from study participants?

☐ Oral Consent

☐ Written Consent

☐ Anonymous survey questionnaire (covering letter required, no consent forms needed)

☐ Other (Please Specify)

How and where will consent/permission be recorded?

Have you attached an informed consent form to your application? ☐ Yes ☒ No

5. SPONSORSHIP OF RESEARCH

If your research is sponsored, is there any potential for conflicts of interest?
If your answer is YES, please complete below

4.1 Is there any existing or potential conflict of interest between a research sponsor, academic supervisor, other researchers or participants?		NO
4.2 Will information that reveals the identity of participants be supplied to a research sponsor, other than with the permission of the individuals?		NO
4.3 Does the proposed research potentially conflict with the research of any other individual or group within the University?		NO

If you have answered **YES** to any of these questions, please describe how you plan to address these issues (append to form)

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6. RISK TO PARTICIPANTS
Does the proposed research pose any physical, psychological, social, legal, economic, or other risks to study participants you can foresee, both immediate and long range? (please select) ☐ Yes ☒ No **If yes, answer the following questions:** 1. Describe in detail the nature and extent of the risk and provide the rationale for the necessity of such risks 2. Outline any alternative approaches that were or will be considered and why alternatives may not be feasible in the study 3. Outline whether and why you feel that the value of information to be gained outweighs the risks
1.
2.
3.

I certify that I have read the Commerce Faculty Ethics in Research policy ☒ (http://www.commerce.uct.ac.za/Pages/ComFac-Downloads)

I hereby undertake to carry out my research in such a way that

- there is no apparent legal objection to the nature or the method of research; and
- the research will not compromise staff or students or the other responsibilities of the University;
- the stated objective will be achieved, and the findings will have a high degree of validity;
- limitations and alternative interpretations will be considered;
- the findings could be subject to peer review and publicly available; and
- I will comply with the conventions of copyright and avoid any practice that would constitute plagiarism.

Signed by:

	Full name and signature	Date
Principal Researcher/Student: Mandla Sibiya		17 June 2022

This application is approved by:

Supervisor: Prof Latif Alhassan		17th June 2022
Departmental Ethics Rep	B.Zolfaghari	19th June 2022

Questionnaire checklist on next page