Credit risk modelling for private firms under distressed economic and financial conditions: evidence from Zimbabwe

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Declaration

I, **Frank Ranganai Matenda (student number 217081687)**, declares that this thesis titled **"Credit risk modelling for private firms under distressed economic and financial conditions: evidence from Zimbabwe"** and the material enclosed in this PhD thesis are an outcome of my original empirical research work. I hereby proclaim that:

- This research project was conducted when I was a PhD (Finance) candidate at the University of KwaZulu-Natal;
- The research work has not been previously submitted in its totality, or in part, at any other institution for the award of any degree;
- I have acknowledged all sources through referencing and citations; and
- I authorise the University of KwaZulu-Natal to replicate for research purposes either the whole or any section of this thesis in any way possible.

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22/01/2021

Date

Publications associated with this research

Chapters two, three, four and six of this PhD thesis have been published as:

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Dedication

My wife, Mirriam, and daughter, Samantha.

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Abstract

Since the outburst of the recent 2007 - 2008 global financial and economic crisis, modelling of credit risk for private non-financial firms under economic and financial stress has been receiving a lot of regulatory and scientific attention the world over. Nevertheless, the quandary is that there seems to be no well-defined estimation procedures and industry consensus on how to incorporate economic downturn conditions in private firm credit risk models, which have led to the introduction of diverse default probability, exposure at default and rate of recovery prediction methodologies. Moreover, there is no consensus on which predictor variables have the most significant impact on private firm credit risk under downturn conditions. This study strives to design forecasting models in order to estimate key credit risk components (default probability, recovery rate and exposure at default) for private non-financial firms under downturn conditions in a developing economy. The main aim of the thesis is to identify and interpret the drivers of probability of default, recovery rate and credit conversion factor. In the first part, the study reviews literature using a scoping review framework in order to identify the reasons and motives for research, emerging trends and research gaps in modelling bankruptcy risk for private non-financial corporations in developing economies. The second part of the thesis creates stepwise logit models to detect the default probability for privately-owned non-financial corporates under downturn conditions in a developing country. In the third section of the study, stepwise logit models are designed to separately forecast probability of default for audited and unaudited privately-traded non-financial corporations under downturn conditions in a developing economy. The fourth part of the thesis develops stepwise Ordinary Least Squares regression models to predict workout recovery rates for defaulted bank loans for private non-financial corporates under downturn conditions in a developing market. In the fifth section of the study, stepwise Ordinary Least Squares regression models are developed to estimate the credit conversion factor to precisely predict, at the account level, the exposure at default for defaulted private non-financial corporations having credit lines under downturn conditions in a developing economy. To fit the models, the study adopts unique real-world data sets pooled from an anonymised major Zimbabwean commercial bank. This study finds that the forecasting of probability of bankruptcy for private non-financial corporates in developing economies is an appropriate discipline that has not been properly studied and has some distinctive and unexplored zones due to its complexity and the diverse

business ethos of private firms. The thesis discovers that accounting information is imperative in predicting the default probability, rate of recovery and exposure at default for Zimbabwean private non-financial corporations under downturn conditions. Further, the study reveals evidence indicating that the forecasting results of the designed credit risk models are improved by incorporating macroeconomic variables. The incorporation of macroeconomic factors is vital since it enables stress testing and provides a way of modelling the default probability, recovery rate and exposure at default under downturn conditions. In light of these findings, it is recommended that firm and/or loan features, accounting information and macroeconomic factors should be adopted when predicting credit risk parameters for private non-financial corporates under downturn conditions in a developing country.

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List of acronyms

AAG	Age of account at default
AG	Age of the firm
AIRB	Advanced internal ratings-based approach
AP/NS	Accounts payable/net sales
AR/NS	Accounts receivable/net sales
AUF	Addition utilisation factor
BB	Budget balance
BCBS	Basel Committee on Banking Supervision
BD/TA	Bank debt/total assets
BIS	Bank for International Settlements
CA/CL	Current assets/current liabilities
CA/TA	Current assets/total assets
(CA-CL)/TA	(Current assets – current liabilities)/total assets
CCF	Credit conversion factor
CL/TA	Current liabilities/total assets
CTV	Collateral value
EADF	Exposure at default factor
EBIT/EQ	Earnings before interest and tax/equity
EBIT/TA	Earnings before interest and tax/total assets
EBIT/TL	Earnings before interest and tax/total liabilities
EQ/TA	Equity/total assets
FIRB	Foundation internal-ratings based
FN	False negative
FP	False positive
GDP	Gross domestic product
GNIC	Gross national income per capita growth
IAS 9	International Accounting Standard 39 Financial Instruments
IASB	International Accounting Standards Board
IFRS 9	International Financial Reporting Standard 9: Financial Instruments
INF	Inflation rate

INT	Interest rate
IRB	Internal ratings-based approach
LEQF	Loan equivalent exposure factor
LMP	Loan maturity period
LN	Loan amount
LwP	Length of the workout process
MAE	Mean absolute error
NC	Number of creditors
NS/NSLY	Net sales/net sales last year
NS/TA	Net sales/total assets
(NS-MC)/PC	(Net sales – material costs)/personnel costs
OBI/TA	Ordinary business income/total assets
OLS	Ordinary least squares
ON	Observed negative
OP	Observed positive
PDE	Public debt
PN	Predicted negative
PP	Predicted positive
RBZ	Reserve Bank of Zimbabwe
RGDP	Real gross domestic product
RMSE	Root mean squared error
RWAs	Risk-weighted assets
SE	Standard error
SD	Standard deviation
SD/TA	Short-term debt/total assets
SMEs	Small-to-medium enterprises

TA	Total assets
TL/EQ	Total liabilities/equity
TL/TA	Total liabilities/total assets
TL/TLLY	Total liabilities/total liabilities last year
TN	True negative
TP	True positive
TwB	Time with the bank
UK	United Kingdom
UR	Unemployment rate
US	United States

Chapter 1: Introduction

1.1 Introduction

The management of credit risk has become a crucial and challenging exercise in business and finance due to the current financial volatilities in the credit markets. Basically, credit risk is defined as the likelihood of incurring a loss that emanates from the failure of an obligor to fulfill its contractual obligations according to predefined terms (Yuksel, 2017; Baesens, Roesch and Scheule; 2016; Basel Committee on Banking Supervision, 2006). Falling costs of buying and selling securities, phenomenal developments in financial engineering, and the exponential explosion of new financial products have progressively exposed financial institutions to diversified credit risk structures (see, for instance, Bussmann et al., 2020; Copgemini Consulting Technology Outsourcing, 2014; Pezzuto, 2012; Miele and Sales, 2011; Swagel, 2009). Various international regulatory frameworks, e.g., Basel II/III Capital Accord and International Financial Reporting Standard 9: Financial Instruments (IFRS 9), have been proposed to alleviate the negative consequences of credit risk on the financial landscape. Several authors (see, for instance, Macaro, Cannizzaro and Garla, 2020; von Solms, 2020) have indicated that regulatory frameworks in the international banking industry are in a never-ceasing condition of influx. Financial institutions, especially in developing economies, often struggle to conform to these rules (see, for example, Ferreira, Jenkinson and Wilson, 2019; Ozili, 2019). von Solms (2020), Chaikovska (2019) and Losiewicz-Dniestrzanska (2015) showed that non-compliance to international regulatory standards threatens the very survival of financial institutions.

Considering their type of business, banks are significantly exposed to credit risk (Yuksel, 2017; Baesens, Roesch and Scheule, 2016; European Banking Authority, 2016). Therefore, it is crucial to create precise and robust credit risk models. Regulatory innovations presented by Basel II/III and IFRS 9 highlight the significant role of credit risk assessment. Credit risk assessment usually takes the form of the estimates of key credit risk components: default probability, recovery rate (where loss given default = 1 – rate of recovery) and exposure at default. Global Public Policy Committee (2016) defined default probability as the likelihood of a default across a specific time period. Account default refers to circumstances where a borrower is not likely to settle its credit commitments or more than 90 days past due on any substantial credit commitment

(Schutte et al., 2020; Basel Committee on Banking Supervision, 2006). Yao (2015) noted that loss given default is an outstanding amount a financial institution expects to lose when an obligor defaults. On the other hand, recovery rate refers to a proportion of exposure recovered throughout the workout process. Bandyopadhyay (2016), Scandizzo (2016) and Basel Committee on Banking Supervision (2011, 2006) posited that exposure at default refers to the total exposure a financial entity faces on a debt facility when a borrower defaults.

Exposure at default, rate of recovery and loss given default are analogous in the sense that their values are only estimated when default occurs. Loss given default is estimated at some time after default, while exposure at default is determined when the account goes into default. Basel II/III Advanced Internal-ratings Based (AIRB) approach permits financial institutions to compute regulatory capital levels (that offer a safety cover against unexpected losses) premised on their internally calculated values of the default probability, exposure at default and recovery rate or loss given default. Credit portfolios' expected and unexpected losses are estimated premised on the estimations of the above key credit risk components (see, for instance, Canals-Cerda, 2020; Schutte et al., 2020; Osipenko, 2018). Yao (2015) posited that for one to better apportion capital, assess prices of financial instruments precisely and manage credit exposures, it is essential to design appropriate advanced internal quantitative models.

The three key credit risk parameters have been selected mainly because of the increased inspection by the regulators and supervisors on the banking industry since the occurrence of the recent 2007 – 2008 universal financial and economic crisis and augmented pressure placed on financial institutions by the regulators to adopt Basel II/III AIRB approach. Baesens, Roesch and Scheule (2016) stated that the recent 2007 - 2008 world-wide financial and economic crisis was mainly caused by credit risk. They further highlighted that against a background of the current universal economic and financial crisis, prudential regulators augmented credit risk model necessities and demanding standards are being applied worldwide. Therefore, the banking industry is continuously searching for precise and robust probability of default, exposure at default and rate of recovery models. In support of this, Baesens, Roesch and Scheule (2016) posited that the designing of more accurate credit risk models would keep model developers busy for years to come.

This thesis designs forecasting models for the default probability, recovery rate and exposure at default for privately-controlled non-financial corporations under downturn conditions in a developing country (Zimbabwe). Its coverage embraces data analysis and pre-processing, default probability, exposure at default, and rate of recovery prediction. The research project pays central attention on identifying and interpreting the determinants of default probability, rate of recovery and exposure at default models for Zimbabwean private non-financial corporations that are under downturn conditions.

1.2 Background and motivations

Basel Accords (II and III) proposed that banks need to hold sufficient capital that provides cushion in case of credit losses premised on the assessment of their credit exposures. Therefore, banks need to predict the default probability, exposure at default and rate of recovery or loss given default for financial instruments since their estimates are vital in forecasting both expected and unexpected losses and in computing the regulatory and economic capital levels. Regulatory capital is the quantity of capital a bank is mandated to possess by the regulators, while economic capital refers to the sum of capital a financial institution believes it needs to hold to safeguard its depositors (Engelmann and Pham, 2020; Tallau, 2020; Yao, 2015). In other words, Baesens, Roesch and Scheule (2016) proffered that the economic capital refers to the volume of capital a financial institution possesses premised on its internal modelling approach and policy. The accuracy of regulatory and economic capital allocation can be enhanced with more exact estimations of default probability, exposure at default and rate of recovery. Moreover, accurate forecasts of default probability, exposure at default and rate of recovery or loss given default play a vital part in investing, lending, trading of financial instruments and pricing of financial assets, among others. (see, for instance, Yao, 2015). It is worth noting that errors in predicting credit risk components are damaging to the banks.

From the time of occurrence of the recent 2007 – 2008 world-wide economic and financial crisis, default probability, exposure at default and rate of recovery values for corporate bank loans have been increasing. Consequently, several studies dealing with the theme of corporate credit risk modelling have been generated. In undeveloped markets, several financial institutions often struggle to design formal credit risk models that are extensively used in developed countries. Challenges include scarcity of data,

shallow and imperfect financial markets, inadequate technical capacity, prevalence of institutional and legal barriers that prevent the free flow of information and lack of extensive penetration by local and external rating firms (see, for instance, Ferreira, Jenkinson and Wilson, 2019; Ozili, 2019; Rylov, Shkurkin and Borisova, 2016). These challenges encourage many financial institutions in developing economies to rely on unfitting informal credit risk models that may not produce credible results and, consequently, expose them to high credit risks.

A majority of studies have been dedicated to credit risk models for publicly listed corporations in advanced countries due to the extensive accessibility of dependable and comprehensive data (see, for instance, Charalambakis and Garrett, 2016). Credit risk modelling literature for privately-traded corporates is generally restricted, and that for such companies in undeveloped countries is even more restricted (Huang et al., 2020). Interestingly, the extant literature on private firm credit risk modelling is primarily dedicated to advanced economies (see, for example, Bussmann et al., 2020; Bauweraerts 2016; Falkenstein, Boral and Carty, 2000). Nevertheless, implementing models created for advanced economies on developing economies does not always give credible results (see, for instance, Ashraf, Felix and Serrasqueiro, 2019; Rylov, Shkurkin and Borisova, 2016), since the economic structures of these economies are considerably dissimilar (Rylov, Shkurkin and Borisova, 2016; Fedorova, Gilenko and Dovzhenko, 2013). Undeveloped economies, for instance, depend on primary commodity exports to get foreign currency and, bank on imports for some basic food supplies and energy. Hence, developing economies are exposed to more challenges when dealing with booms emanating from commodity price surges and exogenous shocks which seem insignificant but frequently generate mayhem in undeveloped markets. In the same accord, a number of authors (see Altman, 2018; Takahashi, Taques and Basso, 2018; Slefendorfas, 2016) indicated that each country has its unique characteristics. Hence, credit risk models developed specifically for individual economies outdo universal models.

Examining credit risk for private corporations in developing economies is crucial for a number of reasons. Private firms, particularly small-to-medium enterprises (SMEs), are the dominant firms in developing markets, perhaps because developing markets are characterised by underdeveloped local equity markets. For example, Organisation for Economic Cooperation and Development (2015) observed that 99.9% of corporates in Greece are SMEs. Private corporations promote economic growth and development and

financial and technological innovations and they reduce unemployment rates in undeveloped countries (Foghani, Mahadi and Omar, 2017; Organisation for Economic Co-operation and Development, 2017; Wang, 2016). Majoni, Matunhu and Chaderopa (2016) and Chiwara (2015) indicated that SMEs are accountable for more than 60% of total employment, gross domestic product (GDP) and tax base in Zimbabwe. Private corporates also represent the common type of firms that eventually fail in developing markets. Given that in the credit portfolios of most banks private corporate loans contribute a large portion, any rise in the quantity of defaulted private corporates in the credit portfolios of banks may cause instability in the financial services sector. Further, given the economic contribution of corporates, Bauweraerts (2016) and Eckbo, Thorburn and Wang (2014) noted that corporate failure is associated with high social and economic costs.

Privately-owned corporations are not the same as publicly traded companies since they are smaller, depend more on bank loans, use more leverage and trade credit, invest more, and are associated with high costs of borrowing (Asker, Farre-Mensa and Ljungqvist, 2012; Gao, Hartford and Li, 2012; Michaely and Roberts, 2012). Moreover, public and private corporations are affected by different regulatory and environmental variables (Hope, Thomas and Vyas, 2013; Falkenstein, Boral and Carty, 2000). The significance of this observation is that credit risk models premised on data pooled from public corporates and applied to private firms will likely distort real credit risk estimates.

Collecting credit risk information and data for private corporations is challenging since their stocks are not traded on stock exchanges (Charalambakis and Garrett, 2019). This shows that the financial records and statements of borrowers that are retrieved from banks are the primary sources of credit risk data and information for private corporations. Hence, estimating default probability, exposure at default and rate of recovery for private corporates is essential since it helps banks to design the supply of credit, collections and cost of credit policies, and generate credit terms to private corporations (see, for instance, Charalambakis and Garrett, 2019). Additionally, evidence on the forecasting performance of default probability, exposure at default and rate of recovery models for privately-traded corporations offers more light on financial ratios' ability to estimate default probability, exposure at default and rate of recovery.

The predictive ability of statistical techniques to model credit risk is based on the presumption that the past association between the covariates of the developed models and the dependent variables will remain the same in the time to come (Hayden, 2011). Nonetheless, several studies (see, for instance, Takahashi, Taques and Basso, 2018; Singh and Mishra, 2016; Smaranda, 2014 and Hayden, 2011) suggested that this supposition would not remain unchanged for long given an extensive variety of possible happenings that can take place in the financial markets, for example, changes in accounting policies of companies, financial and economic crises, structural disruptions in certain industries and introduction of regulatory documents. The coefficients of the credit risk models are sensitive to these probable events that can take place in the financial markets. Therefore, due to changes in time horizons, financial situations and economic conditions, the applicability and predictive performance of the existing corporate credit risk modelling frameworks in new settings becomes an empirical problem that needs to be addressed in modern-day finance. It is necessary to frequently re-calibrate and re-validate credit risk techniques taking into account new settings or events to ensure that their forecasting abilities do not diminish.

Macroeconomic variables considerably influence credit risk (Moudud-Ul-Huq, Akter and Biswas, 2020; Mubin and Sugara, 2020; Koju, Koju and Wang, 2019; Castro, 2013). Therefore, since the outburst of the recent 2007 - 2008 universal financial and economic crisis, modelling of corporate credit risk under economic and financial stress has been receiving a lot of regulatory and scientific attention the world over. Regulatory innovations presented by Basel Accords (II and III) and IFRS 9, erroneous evaluation of corporate credit risk and associations between derivatives, corporate loans and bonds have promoted corporate credit risk modelling under economic and financial stress. The two terms, financial crisis and economic crisis, are used to describe an economy's poor status. Claessens and Kose (2013) defined crises as severe exhibitions of the connections linking the real economy and the financial industry. Therefore, an understanding of financial crises requires comprehension of macro-financial associations.

A financial crisis refers to a financial market disorder that is usually associated with firstly, a rapid, huge and extensive fall in prices of financial assets (for example, falling bond and stock prices, declining loan market values or crumpling exchange rates), inferring a huge and swift rise in interest rates on financial assets (for instance, abruptly increasing interest rates on bonds, loans or money market investments). Secondly, there

is a swift, huge and prevalent fall in prices of real assets (for example, falling prices of real estate or plummeting real capital market prices) (Radke, 2005). Claessens and Kose (2013, pp. 4-5) proposed that a financial crisis is usually related with at least one of the following events:

- significant changes in asset prices and credit volume;
- significant balance sheet problems;
- extreme disturbances in the financial intermediation process and the provision of financing from external sources to several players in the economy; and
- substantial government assistance, usually in the form of recapitalisation and liquidity support.

Generally, a financial crisis involves problems in the banking and finance industry. This shows that financial crises are classically multidimensional. For detailed expositions on the types of financial crises, see Reinhart and Rogoff (2009), Radke (2005) and references therein.

Hadziahmetovic, Halebic and Colakovic-Prguda (2018) suggested that an economic crisis, in economic sciences, is a time horizon of substantial negative growth in economic development of a nation. The authors further posited that an economic crisis could affect one or more countries, a single economic branch throughout the world or the entire world economy. Financial Crisis Inquiry Report (2011) indicated that an economic crisis is a condition where an economy experiences an abrupt downturn due to a financial crisis. Concerning their influence on real economic activity, financial crises can be categorised into two classes, that is, spurious financial crises and systemic financial crises (Radke, 2005). The author posited that a systemic financial crisis is a condition in which asset price falls and increasing interest rates lead to, firstly; an extensive distraction of the ability of financial markets to apportion financial resources into the most efficient production prospects because of an overall liquidity crunch or because of disorder of the payment system and, secondly; real economic downturns or even depressions and deflation by creating extensive failures among financial and non-financial corporations and downfalls in aggregate demand. Radke (2005) also proffered that a spurious financial crisis refers to a state in which asset price falls and interest rates increase abruptly. Firstly, it does not hinder the ability of financial markets to channel financial resources efficiently and efficiently from surplus units to deficit units as disorders are constrained to certain markets, agents or sectors. Secondly, it does not

result in real economic downturns as financial market instabilities are not conveyed into the real sector. For more expositions on the financial crises' influences on the activities in the real economy, the interested is referred to Radke (2005) and references therein.

Hadziahmetovic, Halebic and Colakovic-Prguda, (2018) propounded that recent 2007 – 2008 macroeconomic crisis influenced the entire world economy. The authors observed that the macroeconomic crisis led to low values of major macroeconomic variables such as GDP, balance of payments, investments, currency exchange rates, foreign exchange, government and personal consumption, employment, wages, demand and production. Likewise, in a country, an economic crisis directly influences key economic operations (see Hadziahmetovic, Halebic and Colakovic-Prguda, 2018). A number of authors (see, for instance, Isaksen, 2019; Hadziahmetovic, Halebic and Colakovic-Prguda, 2018; Schoen, 2017; Blinder, 2013) argued that in a country a macroeconomic crisis is usually characterised by slowing GDP growth or GDP contraction, liquidity shortages, high levels of unemployment rates, low production levels, and economic fluctuations resulting from deflation or inflation.

There is a wealth of evidence that indicates that under downturn conditions, the underlying risk of loan portfolios increases dramatically (see, for example, Betz, Kellner and Rosch, 2018; Canals-Cerda and Kerr, 2015a, 2015b; Leow and Crook, 2014). Several authors (see, for instance, Canals-Cerda and Kerr, 2015a, 2015b) highlighted that when forecasting credit risk components, downturn conditions are supposed to be considered in order to avoid the generation of imprecise estimates. The incorporation of macroeconomic variables improves the forecasting results of default probability, exposure at default and rate of recovery (see, for example, Charalambakis and Garrett, 2019; Bellotti and Crook, 2012; Moral, 2011). Nevertheless, the predicament is that there are no well-defined estimation procedures and industry consensus on how to incorporate economic downturn conditions in credit risk models. Also, there is no consensus on which predictor variables have the most substantial influence on corporate credit risk metrics in the context of downturn conditions, resulting in diverse default probability, exposure at default and rate of recovery prediction methodologies. Moreover, since the recent 2007 - 2008 global economic and financial crisis, financial institutions are constantly under pressure from regulators to implement the principles of Basel II/III and IFRS 9. Nonetheless, these regulatory frameworks introduce new ideas in credit risk modelling, for which no precise implementation procedures are illustrated.

This thesis contributes to credit risk modelling discourse by designing models for and analysing the determinants of default probability, recovery rate and exposure at default for private non-financial firms under financial and economic stress in Zimbabwe. The author believes that no such experimental analysis has been conducted for Zimbabwean private corporations. Zimbabwean financial institutions have been craving country-specific credit risk models at the expense of universal credit risk models. Insufficient technical capacity and scarcity of data have however, been responsible for the few attempts to develop credit risk models for Zimbabwean private corporates. Corporate failure prediction studies in Zimbabwe are substantially focused on financial institutions (see Gumbo and Zoromedza, 2016) and public corporations (see Dondo, 2019). Although macroeconomic variables are imperative in estimating company failure, these corporate failure prediction studies only focused on firm and loan characteristics and financial ratios. Further, the current author has not come across any study which models recovery rate and exposure at default specifically for Zimbabwean private corporates.

Zimbabwe offers a thrilling and challenging case study in examining credit risk for private corporations under downturn conditions in developing economies. Private firms are the dominant corporates in Zimbabwe, and over the past two decades, Zimbabwe has witnessed severe and elongated downturn conditions that have contributed to significant deindustrialisation and informalisation of the economy (Gudhlanga and Madongonda, 2019; Rogerson, 2016; Mpofu, 2015; Ndiweni and Verhoeven, 2013; Sikwila, 2013). To stabilise the economy, the country phased out the Zimbabwean dollar in 2009 and adopted a currency basket that encompassed the South African rand, euro, Botswana pula, British pound and US dollar (Pasara and Garidzirai, 2020 and references therein). Further, the central bank, the Reserve Bank of Zimbabwe (RBZ), delivered a monetary policy statement which added the Australian dollar, Japanese yen, Chinese yuan and Indian rupee into the basket of multi-currencies in January 2014 (Pasara and Garidzirai, 2020; The Institute of Chartered Accounts of Zimbabwe, 2018). At the beginning, the US dollar and the South African rand were the most used. However, the US dollar got more dominance and materialised as the functional and presentation currency for firms and monetary authorities (Public Accountants and Auditors Board, 2018; The Institute of Chartered Accounts of Zimbabwe, 2018). Masiyandima et al. (2018) noted that the US dollar's emergence as the key currency induced negative and low rates of inflation, which negatively affected the economy’s growth. The country witnessed twenty-eight successive months of deflation from

October 2014 to January 2017 (Masiyandima et al., 2018). World Bank Group (2020a) indicated that the real GDP growth rate fell from more than 10% per year in 2010 - 2012 to 2% in 2013, recovering to 2.4% in 2014, falling to 1.8% in 2015 to 0.7% in 2016 before recovering to 4.7% in 2017 and falling to 3.5% in 2018, while public debt and budget balance were on average 43.68% of GDP and -4.07% of GDP, respectively, during the sample period. Lack of fiscal cautiousness has led to extended fiscal deficits, resulting in more complex macroeconomic and fiscal difficulties. Savings and foreign and domestic investments have been suppressed and the international debt has fallen into arrears with disastrous consequences. The downturn conditions experienced in Zimbabwe are seldom found in developed markets or even in some developing markets.

On April 17, 2008, the Zimbabwean government indorsed the Indigenisation and Economic Empowerment Act into law to empower indigenous people. Section 3(1) of the Act forces foreigners owning commercial business entities with assets worth at least US$500 000 to relinquish 51% or more of their shares to indigenous Zimbabweans. Thus, most private corporations are owned by indigenous Zimbabweans. The ham-fisted execution of the Act led to a drop in investor confidence, to a fall in aggregate demand for local services and goods, a fall in corporate performance and deterioration in economic growth and development, resulting in the failure of several private corporations.

The RBZ is the chief institution that regulates and supervises the Zimbabwean banking industry which is commercial bank dominated in terms of total deposits, total assets and total loans and advances (Reserve Bank of Zimbabwe, 2018). The Reserve Bank of Zimbabwe (2018) indicated that commercial banks were responsible for 84.44% of total deposits, 83.74% of entire assets and 68.71% of overall loans as of December 31, 2018. The ownership of these commercial banks is spread among foreign nationals, government and local individuals and corporations. To align themselves with the international regulatory standards, Zimbabwean banks are implementing Basel II rules, fronted by the RBZ. Nonetheless, several banks, mostly local and government-owned banks, do not have the adequate technical capacity to adopt Basel II/III, primarily because of the economic and financial difficulties that have bedevilled the economy.

1.2.1 Basel Capital Accords

Despite banks being exposed to a multiplicity of risks due to their business nature, they are largely exposed to credit risk. With the aim of investment or lending, banks attract

withdrawable on demand deposits from the public. For this intermediation process to happen, market participants need to be confident that the banking system and the banks are stable and that they can withdraw their funds whenever they need to do so. Therefore, it is crucial to prevent the loss of trust and confidence in the banking system because it has some serious adverse effects on the whole economy. The major aim of regulatory bodies is to fortify trust and confidence in the banking system by strengthening banks' stability and soundness and protecting depositors and the banking system from calamitous changes that can negatively affect the very survival of banks.

Under the auspices of the Bank for International Settlements (BIS), the Basel Committee on Banking Supervision (BCBS) proposed Basel Capital Accords to strengthen the risk management exercises of internationally active banks. The BCBS was created by the G-10, i.e., Group of Ten, countries' central bank Governors in 1974 (see Baesens, Roesch and Scheule, 2016) as a result of severe instabilities in global banking and currency markets. The BCBS has its headquarters at the BIS in Basel, Switzerland, where the members frequently meet.

In this subsection, the study provides a synopsis of Basel Capital Accords (I, II and III) and highlights the association between Basel Accords and IFRS 9. Baesens, Roesch and Scheule (2016) proffered that Basel Accords were introduced for financial institutions to correctly estimate their capital buffers and provisions in order to counter numerous exposures. Basel Accords' impact on credit risk is discussed here.

Basel I

In 1988, Basel I Capital Accord was suggested by the BCBS, focusing mainly on credit risk. Although Basel I was initially destined for G-10 countries' banks, more than 100 nations have implemented it. ElBannan (2017) highlighted that Basel I was intended to strengthen the international banking system's stability and soundness by recommending an adequate level of capital and in diminishing competitive inequalities among international banks that emanate from dissimilarities among country bank-capital regulations. The Basel I guidelines recommended a minimum capital risk-adjusted ratio of 8 % of the risk-weighted assets (RWAs), at least 4% of which must be the core capital component.

Even though Basel I managed to achieve its objectives, it had some weaknesses (see Baesens, Roesch and Scheule, 2016). In Basel I capital adequacy is contingent on credit risk only, notwithstanding the fact that financial institutions are subjected to different

types of risks originating from their trading undertakings and off-balance-sheet events. A capital ratio of 8% is arbitrary and has been a matter of debate since Basel I's introduction. Basel I proposed a fixed capital ratio of 8%, which cannot change even though the risk is dynamic and under certain situations, banks may need to embrace a capital ratio of more than 8% to shield themselves against high risk (ElBannan, 2017). Moreover, Basel I is rigid as it cannot distinguish between borrowers with dissimilar credit ratings and quality. To account for the weaknesses of Basel I Capital Accord, Basel II Capital Accord was presented.

Basel II

Basel II Capital Accord formally known as the "International Convergence of Capital Measurement and Capital Standards: A Revised Framework" was presented by the BCBS in 2004. The Basel II guidelines were presented in order to stimulate the implementation of strengthened risk management exercises by the sector of international banking. Initially, Basel 1 included credit risk, but its amendment in 1996 incorporated market risk. In the computation of capital adequacy ratio, Basel II included credit, market and operational risks. Basel II prescribes minimum regulatory capital requirements each financial institution has to hold to offer cover against unexpected losses. Basically, Basel II encompasses three mutually reinforcing pillars:

Pillar 1: Capital adequacy requirements

Pillar II: Supervisory review

Pillar III: Market discipline

Pillar 1 deals with the capital adequacy levels that banks need to maintain as safety cover against economic loss. It develops and expands the standardised guidelines stated in the Basel I Accord. Under Pillar I, three diverse kinds of risks are incorporated, that is, credit, operational and market risks. Several approaches of computing total minimum capital levels for credit, operational and market risks are proposed in the Basel II document. However, in this thesis, only the credit risk modelling approach is examined. Basel II adopted the following three ways of credit risk modelling:

1. Standardised approach

2. Internal Ratings Based (IRB) approach

a. Foundation approach

b. Advanced approach

These approaches lead to the creation of mathematical credit risk techniques.

Models for predicting credit risk designed in Pillar I are reviewed by the supervisors. The supervisory review procedure of a bank's credit risk models and capital adequacy is deliberated in Pillar II. Pillar II aims to provide supervisory review guidelines, supervisory accountability and transparency and risk management supervision. Supervisors are given authority to evaluate banks' risk management systems, activities, capital assessment policies and risk profiles in order to decide if banks must maintain higher capital levels than those recommended by the Basel II document. Once quantitative models for credit risk have been ratified, they can now be revealed to the market. This is discussed under Pillar III. Pillar III strengthens market discipline through effective public disclosure on areas such as risk exposures, capital adequacy and risk assessment of the institution. Effective public disclosure to the regulators, market, board of directors, among others, stimulates prudent risk management since it promotes sound banking practices. It is worth noting that Pillar III complements Pillar I and Pillar II.

The Basel II Standardised approach is the simplest of the three extensive methodologies to credit risk and is the same as that of Basel I, though more risk-sensitive. Under the Standardised approach, banks implement ratings for their assets and off-balance-sheet items gathered from external credit assessment organisations like credit rating agencies to determine the required capital. Yao (2015) posited that under the Standardised approach, financial institutions adopt the BCBS's capital requirements with reference to each product. Nonetheless, Basel II inspires financial institutions to shift from the Standardised approach to the Internal Ratings-based (IRB) approach. Basically, the IRB approach is divided into two, that is, the Foundation (FIRB) approach and advanced (AIRB) approach, and it allows financial institutions to build and implement internal risk ratings to fluctuating degrees. To determine minimum capital requirements under the FIRB approach, financial institutions are permitted to implement their internal forecasts of probability of default and adopt the supervisory assessments of other risk components in order to evaluate their portfolios' credit risk. The AIRB approach allows financial organisations so as to use their default probability, exposure at default and rate

of recovery forecasts to determine capital requirements. Notably, the BCBS provides capital incentives to banks that adopt a superior AIRB approach rather than a supervisory approach. The default probability, exposure at default and rate of recovery estimates are used in the computation of expected loss and unexpected loss, determination of economic capital, impairment forecasting, and stress testing (see Tong et al., 2016; Yao, 2015). Expected loss is given by:

Expected loss = default probability x loss given default x exposure at default

The recent 2007 - 2008 global financial and economic crisis, chronicled as the greatest financial crisis since the time of the 1929 - 1939 Great Depression (Soros, 2008), revealed the shortcomings of the Basel II guidelines. Chatzigakis (2016) suggested that the Basel II principles failed to adequately deal with the risks that international banks were exposed to. Financial institutions' capital holdings proved to be miserably insufficient in the face of distressed economic and financial conditions. Further, the amount and quality of capital under Basel II were considered insufficient to cover any additional risk since banks, mostly in advanced countries, were over-leveraged, under-capitalised and relied more on short-term funding.

Basel III

To plug-out the weaknesses of the Basel II rule, Basel III guidelines were presented in 2010 with the main business goal being to further improve risk management practices for international banks (Baesens, Roesch and Scheule, 2016; Chatzigakis, 2016) and to minimise the recurrence probability of a crisis of similar magnitude to the recent 2007 - 2008 one. Baesens, Roesch and Scheule (2016) and Chatzigakis (2016) posited that the Basel III framework was suggested as a direct answer to the recent 2007 – 2008 global economic and financial crisis. The Basel III guidelines were introduced as an extension of Basel II (Baesens, Roesch and Scheule, 2016 and Danila, 2012). Therefore, banks are anticipated to execute the Basel III guidelines as add-ons to the Basel II processes.

The Basel III guidelines promote a more robust banking system by aiming at capital, leverage, funding and liquidity. They focus on raising the amount and quality of capital, liquidity and leverage principles, amendments in provisioning standards and effective disclosures (see, for instance, ElBannan, 2017 and Roy, Kohli and Khatkale, 2013). Basel III intends to make most banking activities more capital intensive. Baesens, Roesch and Scheule (2016) advanced that Basel III pays close attention to tangible

equity capital because it has the highest ability of absorbing losses. Basel III augments minimum core capital, introduces a capital conservation buffer and recommends a countercyclical buffer (Roy, Kohli and Khatkale, 2013). The Tier I capital was raised to 6% of the RWAs in the Basel III framework from 4% of the RWAs in Basel II. Further, the common Tier I capital ratio in which common Tier I capital comprises common equity, i.e., retained earnings and ordinary stock but excluding preferred stock, was raised to 4.5% of the RWAs in Basel III from 2% of the RWAs in Basel II. In Basel III, a capital conservation buffer covered by ordinary equity was gazetted at 2.5% of the RWAs to be and a countercyclical capital buffer stretching from 0% - 2.5% of the RWAs was introduced.

Baesens, Roesch and Scheule (2016) stated that the Basel III framework emphasises stress testing. Basel III has micro-prudential components that enable risk to be restricted to each financial institution and a macro-prudential overlap that deals with matters concerning the systemic crisis. It increases each bank's shock-absorbing ability and has measures that warrant that the whole banking system does not crush and also that its spill-over influences on the real economy are reduced.

1.2.2 Basel Capital Accords and IFRS 9

Since the 2007-2008 global financial and economic crisis, the International Accounting Standards Board (IASB) and BCBS have spearheaded initiatives to reinforce the financial regulatory system. Gornjak (2017) and Ernst & Young (2014) noted that the recent 2007 – 2008 global financial and economic crisis revealed the shortcomings of International Accounting Standard 39 Financial Instruments (IAS 39). Market participants concluded that IAS 39 was complicated, inflexible, confusing and challenging to employ in treating and reporting risks (see, for example, Gornjak, 2017). Therefore, in 2014, the IASB in reaction to the current 2007 - 2008 universal financial and economic crisis, replaced IAS 39 with a forward-looking IFRS 9. IFRS9 has its focus on the measurement and categorisation of financial assets, hedge accounting and financial instruments impairment. It covers the gap between risk management and accounting. Basel Capital Accords (II and III) and IFRS 9 have some similarities and they complement each other (see, for instance, Miu and Ozdemir, 2017). For example, Miu and Ozdemir (2017) proposed that by leveraging on the AIRB models, financial institutions can reduce their modelling struggles in satisfying IFRS 9 and seize the synergy amongst diverse modelling undertakings within the financial institutions. However, while the implementation of IFRS 9 is mandatory, the adoption of Basel

Capital Accords is optional yet recommended. Captivatingly, regulatory innovations presented by Basel Accords (II and III) and IFRS 9 highlight the significant role of credit risk assessment under downturn conditions.

The regulatory innovations presented by the Basel Accords and IFRS 9 indicated that in order to accurately predict default probability, exposure at default and rate of recovery under downturn conditions, the respective models are required to reflect distressed economic and financial conditions through incorporating macroeconomic factors. However, although there are regulatory requirements, there are no regulatory recommendations for designing the default probability, exposure at default and rate of recovery models under financial and economic stress, exposing financial institutions to wide-ranging possibilities. Also, even though financial institutions are required to provide downturn estimates of credit risk components, it is unclear which determinants of credit risk parameters may best capture downturn conditions.

1.3 Aim

This research project aims to contribute to the discourse of private firm credit risk modelling in undeveloped economies under distressed economic and financial conditions. To do so, the study develops default probability, rate of recovery and exposure at default models for Zimbabwean privately-controlled corporations in the context of distressed financial and economic conditions and compares them in order to determine models with superior predictive abilities. The key aim of this thesis is to identify and interpret the predictor variables of private firm default probability, recovery rate and credit conversion factor.

1.4 Problem statement

Corporate credit risk modelling has been receiving a lot of regulatory and scientific attention since the occurrence of the 2007 - 2008 universal economic and financial crisis. Nevertheless, much focus has been directed towards public firms in developed economies owing to the extensive accessibility of dependable and wide-ranging data and information (see Charalambakis and Garrett, 2016; Mora, 2015). Research work on the credit risk for privately-traded corporations is generally limited, and that for such corporates in developing economies is even more limited (see, for example, Charalambakis and Garrett, 2019; Takahashi and Taques and Basso, 2018). The extant

literature on private firm credit risk modelling is chiefly focused on developed markets (see, for instance, Bauweraerts, 2016; Zhao, Dwyer and Zhang, 2014). Applying models designed for advanced economies to emerging markets does not always produce credible results (Ashraf, Felix and Serrasqueiro, 2019; Rylov, Shkurkin and Borisova, 2016) since these economies' economic structures are significantly different (Rylov, Shkurkin and Borisova, 2016; Fedorova, Gilenko and Dovzhenko, 2013). Using the same reasoning line, Altman (2018) and Takahashi, Taques and Basso (2018) indicated that each country has unique features. Thus, models developed specifically for individual countries outperform general models.

Private corporations are dominant firms in developing economies (Charalambakis and Garrett, 2019 and references therein). Also, private corporates promote economic growth and development and financial and technological innovations, and they reduce unemployment rates (see Charalambakis and Garrett, 2019; Hyder and Lussier, 2016; Organisation for Economic Co-operation and Development, 2015). Given firms' economic contribution, Bauweraerts (2016) and Eckbo, Thorburn and Wang (2014) indicated that failure of firms is associated with high social and economic costs. Several authors such as Charalambakis and Garrett (2019) and Ingermann et al. (2016) proposed that the prediction of credit risk metrics for private firms is of paramount importance because it assists banks to generate the credit supply, collections and the credit cost policies, and to design the credit terms of private firms.

The continuing growth of credit markets, exponential rise in defaults, decline in recovery values and regulatory developments are some of the major issues behind the recent increase in interest in corporate credit risk modelling under downturn conditions in developing countries. However, the predicament is that there seems to be no well-defined estimation procedures and industry consensus on how to incorporate economic downturn conditions in private firm credit risk models, which have led to the introduction of diverse default probability, exposure at default and rate of recovery prediction methodologies. Another problem is that there is no consensus on which determinants have the most significant impact on private firm credit risk under downturn conditions.

Even though privately-traded corporations constitute most firms that eventually fail in Zimbabwe, banks have been competing to advance credit to these firms due to their potential for growth and provision of high returns. Therefore, any increase in the

number of defaulted private corporates in financial institutions' portfolios may cause instability in the banking industry. To reinforce the management of credit risk practices in the Zimbabwean banking industry, the RBZ has been placing increased scrutiny and pressure on financial institutions to implement Basel II/III AIRB approach and IFRS 9. However, a number of financial institutions have been struggling to design the best models possible for default probability, exposure at default and rate of recovery to estimate their minimum capital requirements primarily due to insufficient technical capacity. Consequently, several Zimbabwean financial institutions have been relying on informal credit risk evaluation procedures that may not produce reliable results. Thus, the forecasting of default probability, exposure at default and rate of recovery (with a special focus on identifying and interpreting the drivers of default probability, recovery rate and exposure at default models) for Zimbabwean privately-controlled non-financial firms under distressed financial and economic conditions is an issue that requires an examination.

1.5 Research objectives

In the context of distressed financial and economic conditions, this thesis seeks to achieve the following objectives.

i. To identify the reasons and motives for research, emerging trends and research gaps in modelling bankruptcy risk for private non-financial firms in developing countries.
ii. To assess default probability, rate of recovery and exposure at default models that include unique combinations of firm and loan features, financial ratios and macroeconomic factors for Zimbabwean privately-traded non-financial corporates.
iii. To analyse the most significant explanatory variables of default probability, rate of recovery and exposure at default for Zimbabwean privately-held non-financial corporations.

1.6 Research questions

The study provides answers to the questions below:

i. What are the reasons and motives for research, emerging trends and research gaps in modelling bankruptcy risk for private non-financial corporations in developing countries?
ii. Which models give most precise predictions of default probability, exposure at default and rate of recovery for Zimbabwean privately-traded non-financial corporates under downturn conditions?
iii. What are the most significant explanatory variables of default probability, recovery rate and exposure at default for Zimbabwean privately-held non-financial corporations under financial and economic stress?
iv. Are the predictor variables of default probability for audited and unaudited Zimbabwean privately-controlled non-financial corporations under downturn conditions similar?
v. Does the incorporation of macroeconomic variables result in improved default probability, exposure at default and rate of recovery models?
vi. How well do the designed default probability, exposure at default and rate of recovery models fit into the given data samples?

1.7 Significance of the study

This research project is of great interest to academics, regulators and practitioners.

1.7.1 Practitioners

Practitioners such as risk managers, fund managers, consultants and auditors may use the results of this research project to price corporate bank debts, determine regulatory and economic capital requirements for financial institutions, rate corporate borrowers and assess corporates' financial health status and their future prospects. Moreover, the results of this study could be employed as inputs into stress testing, impairment forecasting, expected and unexpected loss prediction techniques, credit portfolio management, etc. Also, the suggested statistical models could be of substantial value to practitioners when implementing Basel II/III AIRB approach.

1.7.2 Regulators

In providing credit to private firms under distressed financial and economic conditions, this thesis has crucial policy implications that regulatory authorities might find

interesting and helpful. The results of the study provide key inputs when regulators design interventions (for instance, diagnosis, schedules, strategies, reforms, etc.) to improve their supervision processes and strengthen risk management practices for financial institutions.

1.7.3 Academics

The creation of credit risk models from the practical side has attracted many academics into credit risk modelling. This study evaluates and illustrates analytical conceptualisations and lays the foundation for the modelling of private corporate credit risk under economic and financial stress, which may help academics who want to understand credit risk modelling concepts and design their empirical credit risk models. Fusing theory with practice, the study leads academics through the credit risk modelling essentials and demonstrates how it is done. The results are essential in pricing on-balance and off-balance sheet private corporate bank loans, managing risk of private firm credit portfolios and computation of capital requirements levels for banks. Further, the research project reveals areas for further research that academics may pursue to improve credit risk modelling.

1.8 Contributions of the study

The major contributions of this thesis can be divided into five as set out in chapters two to six. To the best of the author's understanding, this study is the first piece of research work to examine credit risk for privately-traded non-financial corporations under distressed economic and financial conditions in a developing country (Zimbabwe). The results of the study are interesting since the majority of the existing studies on private firm credit risk modelling are primarily dedicated to advanced economies. To fit the models, this research project adopts unique real-world cross-sectional data sets pooled from an anonymised major Zimbabwean commercial bank. Macroeconomic values are mined from an online open-source, the World Bank Group. Zimbabwe gives a stimulating and challenging case in examining credit risk for privately-traded non-financial corporations in developing countries. Over the past two decades Zimbabwe has experienced severe and prolonged distressed economic and financial conditions. The distressed economic and financial conditions experienced in Zimbabwe are rarely found in developed economies or even in some developing economies.

Firstly, this research project adds new knowledge to the existing body of bankruptcy literature by conducting a review of literature on privately-owned non-financial firm bankruptcy prediction in developing economies using Arksey and O'Malley's (2005) scoping review framework. Whereas the bankruptcy forecasting literature for publicly-owned corporations has been systematically reviewed in several studies, no systematic review or any other form of literature review has been carried out for privately-traded corporations in developing economies. This scoping review examines the reasons and motives for research, the emerging trends and research gaps in forecasting bankruptcy probability for private non-financial corporations in developing economies. The results of the research project disclose that the prediction of bankruptcy probability for private non-financial corporates in developing economies is an imperative discipline that has not been suitably investigated and has some distinctive and unexplored areas due to its complexity and the diverse business ethos of private corporations. For instance, it is highlighted that the examination of default probability for privately-traded non-financial firms under distressed economic and financial conditions in developing economies is an issue that needs further investigation.

Secondly, stepwise logistic regression models are created, premised on different combinations of financial ratios, firm and loan features and macroeconomic variables, and a stepwise selection of some threshold criteria to predict default probability for privately-held non-financial firms under distressed economic and financial conditions in a developing country (Zimbabwe). The main aim of this thesis is to identify and interpret the predictor variables of private firm default probability. Several new predictor variables are embraced in predicting probability of default and a comprehensive examination of the predictors used in the estimation of default probability is given. The results of the experiment indicate that accounting information is useful in distinguishing between defaulted and non-defaulted privately-held non-financial corporations under distressed economic and financial conditions in Zimbabwe. Further, the study shows that the estimation results of probability of default models for private non-financial firms are enhanced by incorporating macroeconomic factors.

Thirdly, the research project separately predicts probability of default for audited and unaudited privately-owned non-financial corporations under distressed economic and financial conditions in a developing country (Zimbabwe) implementing stepwise logit models premised on diverse combinations of financial ratios, firm and loan features and macroeconomic variables. The main aim of the thesis is to identify and interpret the

drivers of probability of default for audited and unaudited Zimbabwean privately-traded non-financial corporations. A number of new predictor variables are employed in separately predicting probability of default for audited and unaudited corporates and a comprehensive examination of the predictors used in probability of default modelling is presented. The study results show that under distressed economic and financial conditions, accounting information is crucial in distinguishing defaulted and non-defaulted audited and unaudited Zimbabwean privately-traded non-financial corporations, and the forecasting ability of default probability models for audited and unaudited privately-held non-financial corporates is augmented by incorporating macroeconomic variables.

Fourthly, stepwise Ordinary Least Squares (OLS) regression models are designed based on different combinations of firm characteristics, loan features and macroeconomic variables to predict workout recovery rates for defaulted bank loans for privately-traded non-financial corporations under distressed financial and economic conditions in a developing economy (Zimbabwe). The main aim of the research project is to identify and interpret the predictor variables of private firm defaulted bank loans recovery rates. Several new predictor variables are implemented in forecasting the recovery rates and a broad analysis of the adopted predictors in modelling the recovery rates is set out. The thesis reveals that accounting information is valuable in examining the recovery rates for defaulted bank loans for privately-held non-financial corporations under distressed economic and financial conditions in Zimbabwe. Further, the research project discloses that the forecasting results of the recovery rate models are enhanced by incorporating macroeconomic variables.

Lastly, OLS regression models are designed based on diverse mixtures of borrower features, account characteristics and macroeconomic factors to predict the credit conversion factor (CCF) in order to accurately estimate, at the account level, exposure at default for defaulted privately-traded non-financial corporations having credit lines under distressed economic and financial conditions in a developing country (Zimbabwe). The primary emphasis of this thesis is on identifying and interpreting the predictor variables of the CCF for the defaulted privately-owned non-financial corporations with credit lines. A number of new predictor variables are adopted in predicting the CCF and a comprehensive examination of the drivers implemented in the prediction of the CCF is outlined. The study results show that accounting information is essential in examining the CCF for defaulted privately-owned non-financial

corporations with credit lines under distressed economic and financial conditions in Zimbabwe. Moreover, the research project reveals that the CCF models' prediction results and the corresponding exposure at default estimates are improved by incorporating macroeconomic variables.

1.9 Delimitations of the study

This study limited to the designing of default probability, rate of recovery and exposure at default models for Zimbabwean privately-controlled corporations in the context of distressed financial and economic conditions and compares them in order to determine models with superior predictive abilities. The main aim being to identify and interpret the predictor variables of private firm default probability, recovery rate and CCF. To fit the models, this study adopts unique real-world cross-sectional data sets pooled from an anonymised major Zimbabwean commercial bank over the observation period 2010 to 2018. Macroeconomic factors are extracted from the World Bank Group, which is an online open-source. Zimbabwe provides an exciting and challenging case in analysing credit risk for private firms in developing countries. Over the past two decades Zimbabwe has experienced severe and prolonged distressed economic and financial conditions that have contributed to substantial deindustrialisation and informalisation of the economy. The downturn conditions witnessed in Zimbabwe are rarely found in developed countries or even in some developing nations.

1.10 Assumptions of the study

This study employs private firm data and information gathered from an anonymised major Zimbabwean commercial bank. Geographically, it is assumed that the sample data sets adopted in this thesis are an accurate depiction of the Zimbabwean market. Also, it is assumed that the study findings are a fair representation of developing economies experiencing downturn conditions across the globe. The study relied on yearly financial statements of defaulted and non-defaulted private corporations when implementing accounting information and data for privately-traded corporations. It is further presumed that the private corporate's financial statements adopted in this experiment denote a 'fair and true perspective' of the corporations' financial situation.

1.11 Thesis outline

This research project is categorised into seven chapters. The first chapter, chapter one, presents the introduction, the background and motivations of the study, the study's aim, the problem statement, the objectives of the study, the research questions, the significance of the study, the limitations and assumptions of the study, the thesis outline and the conclusion. The main examination follows this introductory chapter in five principal chapters, that is, chapters two to six, which address objectives one to five, respectively. These five principal chapters are presented in manuscript forms.

Implementing a scoping review framework proposed by Arksey and O'Malley (2005), chapter two carries out a review of literature on bankruptcy forecasting for private non-financial firms in developing economies. This chapter examines the reasons and motives for research, emerging trends and research gaps in modelling bankruptcy risk for private corporations in developing countries. Chapter two is segmented into five subsections, i.e., the introduction, the methodology, the literature review, the results and discussion and the conclusions.

Chapter three examines default risk for private firms under distressed financial and economic conditions in Zimbabwe using stepwise logistic regression models and a stepwise selection of some threshold criteria. The key purpose of this chapter is to identify and interpret the drivers of private firm probability of default. Chapter three is divided into five subsections, that is, the introduction, the methodology, the sample and data, the experimental results and the conclusions.

Chapter four separately forecasts probability of default for audited and unaudited Zimbabwean privately-held non-financial corporates under financial and economic stress implementing stepwise logistic regression models. The main intention of chapter four is to identify and interpret the explanatory variables of probability of default for audited and unaudited Zimbabwean privately-owned non-financial corporations. Chapter four is segmented into eight subsections, that is, the introduction, the literature review, the methodology, the data and variables, the experimental results, the discussion, the robustness checks and the conclusions and implications of the study.

Chapter five designs stepwise OLS regression models to forecast workout recovery rates for defaulted bank loans for private non-financial corporates under distressed economic and financial conditions in Zimbabwe. The principal goal of chapter five is to recognise and interpret the predictor variables of private firm defaulted bank loans

recovery rates. This chapter is dissected into six subsections, containing, the introduction, the literature review, the methodology, the sample and data, the empirical results and analysis and the conclusions.

Chapter six creates OLS regression models to estimate the CCF to precisely predict, at the account level, exposure at default for defaulted private non-financial corporations having credit lines under downturn conditions in Zimbabwe. The primary focus of Chapter six is on identifying and interpreting the CCF determinants for the defaulted privately-owned corporates with credit lines. Chapter six is divided into six subsections, which are, the introduction, the literature review, the methodology, the sample and data, the empirical results and analysis and the conclusions.

Finally, chapter seven outlines a summary, conclusions and recommendations of the study. Further, it provides direction for further research. This chapter is segmented into four subsections, namely, the introduction, the thesis summary and conclusions; key findings, implications, contributions and recommendations of the study, as well as the issues for further research.

1.12 Conclusions

Chapter one is introductory. It presented the introduction, the background and motivations, the aim of the study, the statement of the problem, the objectives of the study, the research questions, the study's significance, the limitations and assumptions of the study, the thesis outline and the conclusions. Given the economic importance of private firms and the fact that private corporates represent common companies that eventually fail in developing economies, chapter one revealed that credit risk modelling for private corporations under downturn conditions in undeveloped countries is an imperative exercise in contemporary credit risk management. Nevertheless, the literature on private firm failure is generally scanty due to the restricted access to default data and information for private companies since their stocks are not traded on stock exchanges. The next chapter, chapter two, uses a scoping review framework to carry out a review of literature on bankruptcy forecasting for private firms in undeveloped economies. A scoping review is adopted in the next chapter because it incorporates findings from a variety of diverse study methods and designs, the research area is sophisticated and diverse and has not been expansively reviewed before and it is convenient in providing answers to extensive questions. The main emphasis of the

scoping review adopted in chapter two is to analyse the reasons and motives for research, emerging trends and research gaps in modelling bankruptcy risk for private corporations in developing countries.

Chapter 2: Bankruptcy prediction for private firms in developing economies: a scoping review and guidance for future research

(*This chapter has been published in Management Review Quarterly (see Appendix A2.4)*)

2.1 Introduction

Corporate failure is not preferred by corporate stakeholders and the country at large (Alaka et al., 2015; Hafiz et al., 2015; Tinoco and Wilson, 2013; Xu and Zhang, 2009) since it is associated with significant social and economic costs (Waqas and Md-Rus, 2018; Bauweraerts, 2016; Senbet and Wang, 2012). Also, Doumpos and Zopoudinis (1999) declared that bankruptcy is contagious, that is, firms whose business operations depend on bankrupt corporate's activities may follow in bankruptcy. Thus, in the field of banking and finance, a number of models have been created by practitioners and academics to predict corporate bankruptcy. Nevertheless, since there is no commonly accepted definition of business failure (Papana and Spyridou, 2020; Shi and Li, 2019), there is no generally accepted business failure forecasting model in the extant literature (Shi and Li, 2019). Shi and Li (2019) argued that the business failure definition is indistinct and literature on business failure is very disjointed. Diverse stages of examination, several theoretical frameworks and different definitions of corporate failure make it challenging to compare extant studies (Kucher, Feldbauer-Durstmuller and Duller, 2015). Using the same line of reasoning, Papana and Spyridou (2020) and Balcaen and Ooghe (2006) proposed that the measure of business failure is selected subjectively in the existent literature. Researchers frequently conduct their experiments by examining certain facets or phases of business failure (Dimitras, Zanakis and Zopoudinis, 1996). Several terms that are used to describe business failure in practice, such as bankruptcy and default, are applied interchangeably (Alaka et al., 2018; Obradovic et al. 2018; Appiah, Chizema and Arthur, 2015; Dichev, 1998). Likewise, in this current scoping review, the terms that are applied to designate business failure in reality are used interchangeably.

Since the publication of the classical research works of Altman (1968) and Beaver (1966), financial markets have been experiencing a boom in corporate failure detection literature. A myriad of corporate failure techniques has been generated (see, for instance, Altman, 2018). Of late, with the establishment of advanced computing systems, emergence of vast and specialised databases, exponential increases in

bankruptcy rates, evolving credit risk literature and swift growth of credit derivatives markets, corporate failure forecasting models have become more sophisticated. Corporate bankruptcy models can be classified as accounting-based models (Zmijewski, 1984; Ohlson, 1980; Altman, 1968), market-based models (Merton, 1974) or mixed models (Trabelsi et al., 2015; Chava and Jarrow, 2004). These models describe diverse facets of bankruptcy risk. Accounting-based bankruptcy forecasting models apply accounting data, that is, a set of financial ratios or a sole financial ratio deduced from financial statements (e.g., profitability, liquidity, efficiency and leverage ratios) to forecast firm bankruptcy (Charalambakis and Garrett, 2019). Agarwal and Taffler (2008) proposed that accounting-ratio based models are classically designed by analysing a set of financial ratios with the weightings of ratios assessed on a data matrix of non-failed and failed corporates. Market-based models include market variables, such as stock returns, earnings per share and stock volatilities, in default prediction (Chen and Xu, 2018). These market-based models are usually categorised into structural form models (see, for example, Merton, 1974; Agarwal and Taffler, 2008) and reduced form models (see, for instance, Jarrow and Turnbull, 1995). For more expositions on accounting-based and market based models, see, among other sources, Pozzoli and Paolone (2017), Agarwal and Taffler (2008) and Beaver, McNichols and Rhie (2005). Lastly, Chen and Xu (2018) articulated that mixed models incorporate both accounting information and market information into bankruptcy prediction.

Of late, the level of corporate debts has been generally skyrocketing in both developed and developing economies. The size of the market for "junk bonds" (high-yield) has increased from, in 1978, US$10 billion of fallen angels to around US$1.7 trillion of generally "original issue" high yield in 2017 (Altman, 2018). Cortina, Didier and Schmukler (2018) highlighted that the total volume of debt granted through cross-border and domestic bonds and syndicated loans amplified to approximately 30-fold in developing economies from 1991 to 2014. Moreover, since the recent 2007 – 2008 global economic and financial crisis, the issuing of leverage loans and high-yield bonds has been growing tremendously, with US$200 billion, each year since 2010, of new issues of bonds (Altman, 2018). The author further suggested that this increase has been driven by a benign credit cycle, which in 2017 was in the year number eight. Alfaro et al. (2017), International Monetary Fund (2015) and Bank for International Settlements (2014) observed that after the current 2007 - 2008 universal financial and economic crisis, there has been a swift expansion of credit in developing economies.

Though in developed economies the accumulation of debt has been generally motivated by government debt (Atradius Economic Research, 2016), the corporate non-financial sector has been responsible for the larger portion of the upwelling in leverage in developing markets, which has been accountable for huge increases in international bond granting as well (Atradius Economic Research, 2016; Bank for International Settlements, 2016). Bank for International Settlements (2016) indicated that international and domestic debt of non-financial corporations in developing markets has increased from US$2.4 trillion to US$3.7 trillion and international bonds outstanding rose from US$360 billion to US$1.1 trillion between 2007 and 2015.

This recent increase in corporate debts in developing economies has happened during unprecedentedly loose global economic and financial situations, with low, eye-catching interest rates (Cortina, Didier and Schmukler, 2018). New issues of loans have amplified firm debt ratios to extraordinary levels, as corporations have taken advantage of the atmosphere with low interest rates and easy money. Financial institutions have also been granting loans to the riskiest firms in search of yields. Since financial crises in developing economies are generally preceded by great firm leverage levels, the swift increase in debt borrowing has upraised policy alarms (Herwadkar, 2017; Schularick and Taylor, 2012; Mendoza and Terrones, 2008). Atradius Economic Research (2016) posited that the swift debt accumulation in developing economies has upraised alarms concerning the creditworthiness of their corporate sectors taking into account a progressively challenging environment of lethargic international trade, corporates' deteriorating profitability, low commodity prices, the regularisation of United States interest rates and the depreciation of currencies. Vazza et al. (2019) postulated that developing economies were hard hit by the global economy slowdown resulting from trade conflicts. Interestingly, in emerging markets, risks have increased on a micro level, contingent on the country and the sector in which firms are operating (Atradius Economic Research, 2016). Using the same line of reasoning, Vazza et al. (2019) proffered an argument that waves of downgrades have been restricted to nation-specific proceedings that had been evolving for some time in particular developing economies. The authors further stated that developing economies witnessed the biggest rises in the quantity of downgrades in 2018. For example, the authors reported that firm downgrades in Brazil, Turkey and Argentina more than doubled.

Given the unprecedentedly loose world-wide financial and economic situations and questionable creditworthiness of several firms in developing markets, the current rise in

debt ratios for corporates in developing economies is generally not a favourable atmosphere for credit risk. High firm debt ratios have caused a decline in the financial performance of firms, leading to the distress of non-financial firms and their susceptibility to balance sheet shocks that spread into the banking industry. Hence, the number of corporate defaults in developing economies has been increasing (Vazza et al., 2019). For instance, the authors observed that, in 2018, the speculative-grade default rate increased to 1.3% in developing countries. Moreover, Atradius Economic Research (2016) indicated that corporations in developing economies usually finance themselves using local currencies from local banks in domestic markets. Banks in developing markets have been competing with public markets in financing corporations, in spite of the increase in corporate default and regulatory oversight rules. Since corporate loans contribute a significant portion in the credit portfolios of several banks in developing economies, the rise in the number of defaulted corporations in the credit portfolios of financial institutions has been causing systematic balance sheet problems and instability in the financial services sector. Hence, several banks failed, leading to the breakdown of the channel of credit. The channel of credit breakdown hit harder medium and small corporations because they did not have access to other kinds of credit that huge corporates have access to. Augmented levels of firm debts and elevated corporate defaults in developing markets have not only led to financial instability, they dampened investment and long-term economic growth and development as well.

Therefore, it is imperative to create reliable corporate bankruptcy techniques in contemporary risk management at micro and macro levels. Given the economic importance of corporations, research concerning corporate bankruptcy forecasting is vital for policymakers to stimulate macroeconomic growth and development. Altman et al. (2017) proposed that a well-timed and precise estimation of firm bankruptcy probability plays a vital role in promoting the banking industry's stability since the banking industry seeks to condense the number of non-performing loans so that it increases the profit from credit activities and the banks are interested in reducing their default risk. The world over, the issue of non-performing loans has become a nuisance and has been given high significance by policy makers, e.g., central banks, and is presently being examined with a number of metrics (Manz, 2019). Therefore, bankruptcy forecasting models help banks in assessing the bankruptcy risk of corporations and, in reality, timely forecasting of corporate bankruptcy might assist lenders prevent some of the costs related to bankruptcy (see Tinoco and Wilson, 2013).

Also, bankruptcy forecasting models help financial institutions design policies linked to the provision and cost of credit to corporations, and they are imperative in the determination of capital adequacy, for banks, that cover unexpected future losses. Further, since the owners and managers of corporations become conscious of possible challenges and threats to their corporations, precise prediction of corporate failure could allow corporate owners and managers to take corrective activities and save the corporations from financial insolvency, thereby promoting stability in both the banking industry and corporate non-financial sector.

Although a wealth of academic and practitioner corporate bankruptcy forecasting literature has been put forward, the majority of the research mainly focuses on the bankruptcy detection models for publicly-held corporations in developed countries since reliable and comprehensive bankruptcy data and information for publicly-traded corporates is broadly available (Papana and Spyridou, 2020; Charalambakis and Garrett, 2019; Charalambakis, 2014). Research on bankruptcy forecasting for privately-held corporations is generally limited and is even more constrained for private firms in developing economies. The existing bankruptcy literature on privately-owned corporations is substantially focused on advanced economies (Jensen, Lando and Medhat, 2017; Bauweraerts, 2016; Diekes et al., 2013; Cangemi, Servigny and Friedman, 2003; Falkenstein, Boral and Carty, 2000). Charalambakis and Garrett (2019) highlighted that the scanty literature on private firm failure is attributed to the restricted access to default data and information for private companies since their stocks are not traded on stock exchanges. A number of studies (see, for instance, Ozili 2019; Rylov, Shkurkin and Borisova, 2016), suggested that financial institutions in emerging markets usually have challenges in designing bankruptcy prediction models due to thin and imperfect financial markets, limited data, inadequate technical ability and deficiency of far-reaching penetration by both local and external rating corporates.

There are several reasons why private firm bankruptcy prediction in developing economies is a vital task. Private corporates, particularly small-to-medium enterprises (SMEs), are dominant legal forms of corporations in developing markets (Charalambakis and Garrett, 2019; Jacoby, Li and Liu, 2019; Majukwa, 2019; Slefendorfas, 2016). In support of this, Jacoby, Li and Liu (2019) articulated that Chinese privately-owned corporations account for 99.8% of companies as per China Statistics Yearbook 2012 and Organisation for Economic Co-operation and Development (2015) proposed that 99.9% of corporates in Greece are SMEs. Also, a

number of studies, such as Pertuz and Perez (2021), Charalambakis and Garrett (2019), Majukwa (2019), Altman et al. (2017), Foghani, Mahadi and Omar (2017), Slefendorfas (2016), Charalambakis (2014) and references therein, indicated that private corporations promote economic growth and development, stimulate financial and technological innovations and they reduce unemployment rates in underdeveloped countries. For example, in Greece, SMEs contribute 69% of the value added and are responsible for 84.9% of the labour force (Organisation for Economic Co-operation and Development, 2015). With respect to Zimbabwe, SMEs are accountable for more than 60% of total employment, gross domestic product (GDP) and tax base (Majoni, Matunhu and Chaderopa, 2016; Chiwara, 2015). Despite these economic contributions of private corporations, they represent common companies that eventually fail in developing firms (Bushe, 2019 and Lings, 2014). Further, in spite of the high failure rates of private corporates, financial institutions in developing countries have been competing to advance credit to such corporations because of their potential for growth and provision of high returns, see Voronkova, et al. (2018) and Beck and Cull (2014), among others.

Whereas the bankruptcy forecasting literature for publicly-traded corporates has been systematically reviewed in numerous studies, no systematic review or any other form of literature review has been conducted for privately-owned corporations in developing economies. This study adds new knowledge to the existing body of bankruptcy literature by carrying out a review of literature on privately-owned firm bankruptcy forecasting in developing economies using Arksey and O'Malley's (2005) scoping review framework. The main emphasis of the scoping review is to analyse the reasons and motives for research, emerging trends and research gaps in modelling bankruptcy risk for private corporations in developing countries. The researchers believe that this study is the first piece of research work to conduct such a scoping review. The scoping review concludes that the estimation of bankruptcy probability for private corporates in undeveloped markets is a relevant discipline that has not been appropriately examined and has some unique and unexplored areas due to its sophistication and the different business ethos of private corporations.

The entire chapter is prearranged as below. Section 2.2 discusses the methodology of the study and the review of the selected studies is presented in section 2.3. Results and discussions are outlined in section 2.4. Finally, conclusions are presented in section 2.5.

2.2 Methodology

This study implements a scoping review technique founded on the methodological structure presented by Arksey and O'Malley (2005) to review literature on private firm bankruptcy forecasting in undeveloped economies. The main purpose is to identify reasons and motives for research, establish emerging trends and research gaps in bankruptcy probability prediction for privately-traded corporates in emerging markets. A scoping review refers to a form of research fusion that intents to layout the literature on a specific discipline or research area and offers a chance to detect main ideas, research gaps and forms and fountains of evidence to appraise policymaking, research and practice (see, for instance, Daudt, van Mossel and Scott, 2013; Mays, Roberts and Popay, 2001). In this study, a scoping review approach is adopted due to the following reasons. Scoping reviews examine extant literature and other information sources and usually incorporate findings from a variety of diverse study methods and designs (Davis, Drey and Gould, 2009). Peters et al. (2015) and Mays, Roberts and Popay (2001) indicated that a scoping review can be adopted especially when the research area is sophisticated and diverse or has not been expansively reviewed before. Also, scoping reviews are convenient in providing answers to extensive questions (Sucharew and Macaluso, 2019). Since the extensive scope of the gathered information in this study makes implementing recognised meta-analytic approaches challenging, if not impossible (Sucharew and Macaluso, 2019), a scoping review is a way to go. This shows that a scoping review gives sound and dependable knowledge and minimises bias. For more expositions about scoping reviews, see, Sucharew and Macaluso (2019), Pham et al. (2014), Arksey and O'Malley (2005) and references therein, among other sources.

The methodological structure proposed by Arksey and O'Malley (2005) has the following five phases:

(i) Phase 1: Research question identification,
(ii) Phase 2: Relevant articles identification,
(iii) Phase 3: Study selection,
(iv) Phase 4: Data charting, and
(v) Phase 5: Compiling, summarizing and chronicling the research results.

An additional parallel and optional element concerning the use of a 'consultation exercise' is not performed in this research work.

2.2.1 Phase 1: Research question identification

The initial stage of the scoping review methodological structure presented by Arksey and O'Malley (2005) is to generate the research question to be answered. This directs the way that search plans are designed. The current scoping review attempts to provide answers to the ensuing question: What are the reasons and motives for research, emerging trends and research gaps in modelling bankruptcy risk for private non-financial corporations in developing economies? The author assumes that the research question sustains an extensive approach in order to produce extensiveness of coverage.

2.2.2 Phase 2: Relevant studies identification

To be as all-inclusive as imaginable in choosing primary studies, the primary studies, i.e., published studies, which are appropriate in responding to the research question, are pooled from the following six sources:

- ScienceDirect,
- Google Scholar,
- ResearchGate,
- Google,
- 'snowball' approach, and
- hand-searching of journals.

ScienceDirect, Google Scholar, ResearchGate and Google are nominated because they include numerous articles, some of which are indexed in Web of Science and Scopus and they enable gathering of articles by directly contacting their authors. To guarantee high levels of repeatability, consistency, reliability and quality, only articles pooled from these sources are examined. This warrants the elimination of source bias. Also, studies from all corners of the world are reviewed. Henceforth, geographic bias is eradicated.

Considering budget restrictions and time limitations, the current scoping review includes studies only published between January 2000 and December 2020. The initial date of January 2000 is chosen since it is felt that privately-owned firm bankruptcy prediction research discipline is relatively current as it started to get more scientific and academic research attention after the year 2000 (especially after the occurrence of the recent 2007 – 2008 global financial and economic crisis). A deadline of December 2020 is also set, after which studies would not be incorporated into the analysis since time is restricted. Research articles published in other languages besides English are disqualified from the study due to time and cost associated when translating them (see,

for instance, Pham et al., 2014 and Arksey and O'Malley, 2005). Although these limits are implemented for practical motives, Arksey and O'Malley (2005) posited that it is imperative to note that, that way, appropriate studies may be overlooked.

For electronic databases, the search strategy is generated from the research question. A pilot search strategy is conducted in order to make improvements on the search strategy where needed. Basing on the results from the pilot search strategy, the first search strategy is further polished. The final search inquiry comprises phrases regarded as suitable for describing bankruptcy prediction for private non-financial firms in developing countries: "bankruptcy prediction for private firms in a developing country" or "private firm bankruptcy prediction in a developing country" or "financial distress prediction for private firms in a developing country" or "private firm financial distress prediction in a developing country". The final version of the search strategy is first applied on the Google Scholar database and then used on the other databases. In searching for research evidence for the first time, date limits are placed. On August 02, 2018, the first act of searching for relevant literature was executed in the 3 databases, i.e., GoogleScholar, ScienceDirect and ResearchGate, pooling 11 articles that appear to be suitable for review. Also, a 'snowball' approach was implemented in which citations inside research articles are investigated if they seem appropriate to the study (see, Jaskiewicz and Tulenko, 2012 and Hepplestone et al., 2011). Even though a saturation point was reached at which no new references were being found, the 'snowball' found more references. Six research papers that look appropriate to the study at hand were gathered through the 'snowball' approach.

To improve the aptness of the scoping review, follow-up searches of the literature were performed on 15 August 2019 and 31 December 2020, to find any supplementary literature published after the first act of searching. At this time, Google search with no date boundaries was conducted and only the first 100 articles on each follow-up act of searching, as arranged by Google by applicability, were vetted and 6 prospective studies were pooled. The a priori verdict was gazetted only to screen, on each case, the first 100 studies that are regarded as relevant. This decision was made after realising that much time was needed to vet studies individually and after noting that additional vetting is doubtful to give extra suitable papers (see, Stevinson and Lawlor, 2004). Further, journals were hand-searched to find studies that have been overlooked in the reference list and database searches. Hand-searching of journals approach is adopted in this study

since Arksey and O'Malley (2005) articulated that reference list and database searches may miss other studies. The authors proposed that this can occur because databases (electronic) may be not up-to-date, unfinished or abstracting services can differ in indexing, coverage and information depth. Consequently, 2 potentially suitable articles were pooled from the hand-searched journals. In particular, the two prospective studies were hand-picked from the Journal of International Financial Management and Accounting, and iBusiness.

2.2.3 Phase 3: Study selection

The search strategy picked several inappropriate studies for this review. This is partially caused by the fact that the scoping review had pursued breadth rather than depth. Studies that do not address the main research question are eliminated from the review. Moreover, duplicate references are eliminated physically to guarantee unbiased results.

2.2.3.1 Eligibility criteria

The criteria for including and excluding articles for this review are cautiously selected to permit impartial comparison and guarantee sufficient quality. Arksey and O'Malley (2005) posited that to guarantee reliability in decision-making, the inclusion and exclusion criteria should be premised on the key research question. Portion of the basis for implementing a scoping review method is to allow the incorporation of an extensive assortment of sources which are classified outside the usual peer-reviewed study (Sucharew and Macaluso, 2019). However, to improve the research validity, only peer-reviewed articles are analysed because they are viewed as of superior quality and their contributions are regarded as valid (see, for instance, Pita et al., 2011; Baxter, Glendinning and Clarke, 2008). Studies are worthy of inclusion if they examine bankruptcy probability prediction for private firms in undeveloped countries. Articles that examine bankruptcy prediction for publicly-traded corporates and bankruptcy forecasting for privately-owned corporations in developed economies are excluded from the review. Also, studies published in other languages other than English are not incorporated into the analysis.

2.2.3.2 Title and abstract suitability vetting

As articulated in Pham et al. (2014), the titles and abstracts of studies are appraised in the first stage of vetting to prevent wastage of resources in acquiring research articles that fail to achieve minimum criteria for inclusion. A form for the title and abstract suitability vetting is designed, pretested and revised as required prior to application (see

Appendix A2.1). In some instances, reviewing the title and abstract alone is not enough. Given such situations, the introduction or conclusion or both are reviewed (see, for instance, Pham et al., 2014). When reviewing the introduction or conclusion or both is also not enough, whole research articles are reviewed to deliberate their inclusion in the review. This implies that full texts of these research papers, written in English, are available.

2.2.3.3 Data collection

All citations thought to be suitable after the vetting process are acquired for full-text analysis. For research papers that are not gathered through authors' institutions, efforts are made to get hold of the respective authors and journals for assistance in obtaining these articles. An integrated template is designed to check the suitability of the articles and gather their features, i.e., author(s), publication year, the title of the study, the study's aim, variable(s) adopted, sample, data source(s), technique(s) implemented and study results (see Appendix A2.2). The template is pretested and revised as required prior to application. The suitability and features of each full-text research article are checked and mined. At this stage, full studies are read and the ultimate decision about their suitability for inclusion in the review is made. All articles that fail to meet the criteria of eligibility are dropped at this stage. It is worth mentioning that since studies that examine private firm bankruptcy prediction in developing economies are very limited and hard to come by (see Charalambakis and Garrett, 2019; Charalambakis, 2014), the scoping review adopts a restricted number of articles. The following 12 research articles are ultimately nominated for review: Papana and Spyridou (2020), Charalambakis and Garrett (2019), Jacoby, Li and Liu (2019), Range, Njeru and Waititu (2018), Takahashi, Taques and Basso (2018), Altman et al. (2017), Stojanovic and Drinic (2017), Slefendorfas (2016), Charalambakis (2014), Rim and Roy (2014), Eljelly and Mansour (2001) and Kpodoh (2009) (see Appendix A2.3).

In Figure 2.1 below, the flow of studies from identification to final inclusion is outlined. The original searches (performed in August 2018) and follow-up searches (conducted in December 2020 and August 2019) produced 25 hypothetically appropriate studies. After relevance and deduplication screening exercise, thirteen articles met the eligibility criteria, i.e., 11 premised on title and abstract and 2 based on introduction, and the resultant full-text studies are acquired for further review. One article could not be

acquired due to limited financial resources and, as a result, it is not incorporated into the review. Therefore, only 12 articles are incorporated into the analysis.

2.2.4 Phase 4: Data charting

This stage involves the 'charting' of main pieces of information acquired from the reviewed primary research articles. Ritchie and Spencer (1994) indicated that 'charting' refers to a method for interpreting and synthesising qualitative data by examining, charting and organising material with reference to the main themes and issues. In the narrative review tradition, the 'descriptive-analytical' technique which includes implementing the same analytical structure to all selected articles and ordinary information gathering on each article is adopted in this review (see, Arksey and O'Malley, 2005). Data charted in this study is presented onto a 'data charting form' (see Appendix A2.2). On this chart, the following pieces of information are recorded:

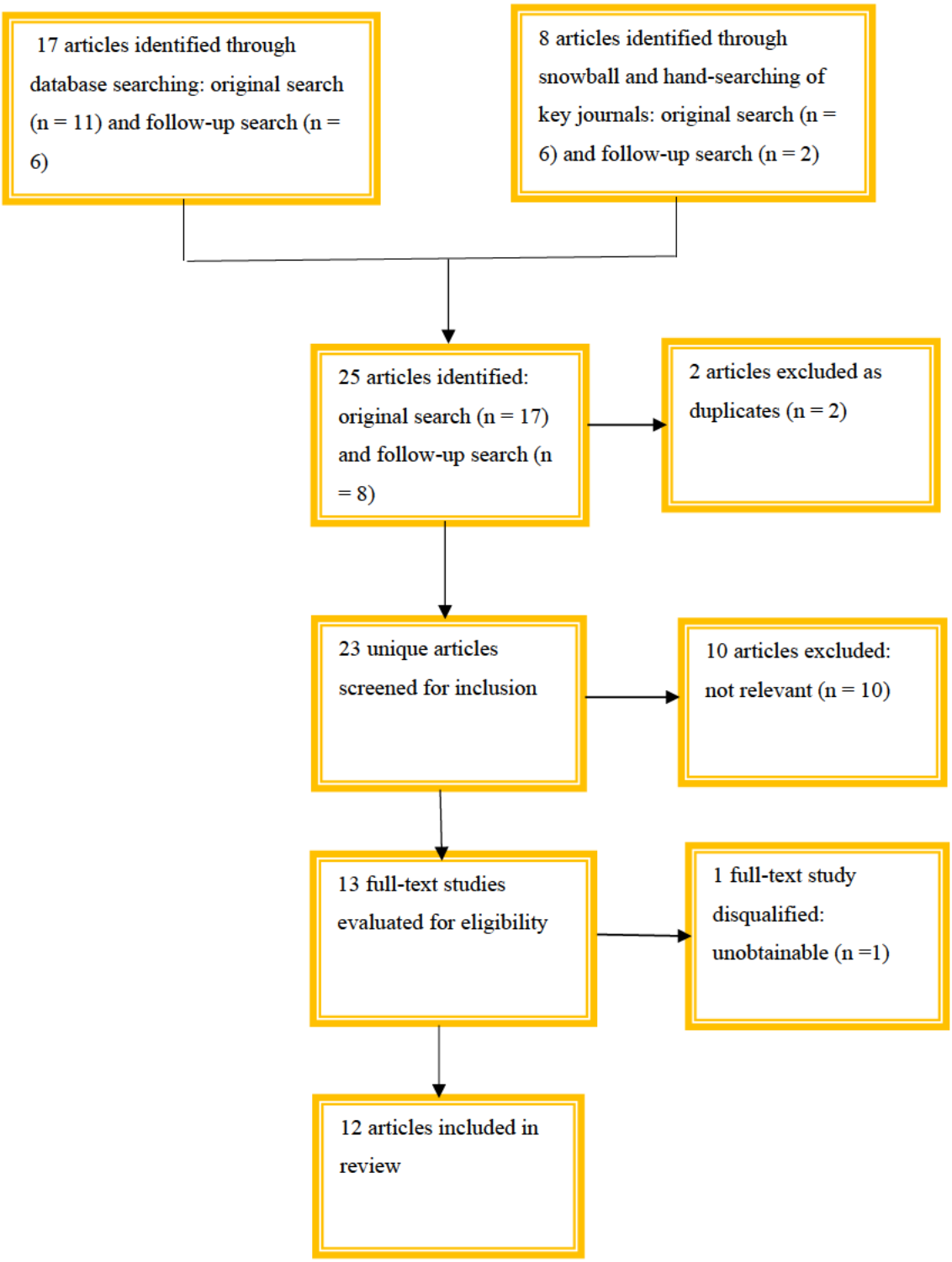
- Author(s),
- publication year,
- the title of the study,
- the study's aim,
- variable(s) adopted,
- sample,
- data source(s),
- techniques implemented, and
- Research results.

These pieces of information make the foundation of this scoping review.

2.2.5 Phase 5: Collating, summarising and reporting the results

This stage comprises the collating, summarising and reporting of the results. Sucharew and Macaluso (2019) argued that a scoping review results usually concentrate on the variety of content found and quantitative examination is frequently restricted to a count of the amount of sources recording a specific recommendation or issue. This scoping review presents an overview of all reviewed material. After information from the articles is charted and a review of selected studies is given, a narrative account of the findings is presented, that is, findings are elucidated and discussions which are supported by the available extensive literature are outlined.

Figure 2. 1 Study selection process flowchart



2.3 Review of selected studies

This study reviews papers published in peer-reviewed journals and a published dissertation, which analysed bankruptcy forecasting for privately-traded corporations in developing economies. Due to limited extant literature on bankruptcy prediction for private firms in developing economies, a published dissertation is included for review. Although dissertations are not peer-reviewed, they may be considered scholarly sources because they are carefully supervised, are comprehensively researched, are directed to an academic audience, are referenced in other scholarly work and they follow research methodology. The reviewed studies were published between January 2000 and December 2020. Of the several articles identified in this review, only 12 articles are selected for review. This section provides a narrative account of the various key characteristics of the reviewed studies, namely, author(s), publication year, the title of the study, the study's aim, variable(s) adopted, sample, data source(s), technique(s) implemented and research results. Table 2.1 summarises the key characteristics, i.e., author(s), publication year, the title of the study, the study's aim, variable(s) adopted, sample and technique(s) implemented, of the articles included in this analysis.

Table 2. 1 Summary of the key characteristics of the reviewed studies

Author(s)(Year): Title	**Aim of the study**	**Variable(s) adopted**	**Sample**	**Technique (s)**
Papana and Spyridou (2020): 'Bankruptcy prediction: the case of the Greek market'	To assess the ability of decision trees, linear discriminant analysis, logit regression and neural networks in forecasting financial bankruptcy applying a Greek data set.	50 financial ratios	100 non-bankrupt and 100 bankrupt small and medium Greek private firms	Decision trees, linear discriminant analysis, logistic regression, neural networks.
Charalambakis and Garrett (2019): 'On corporate financial distress prediction: what can we learn from private firms in a developing economy? evidence from Greece'	To analyse the drivers of financial distress probability for Greek privately-owned corporations	Ratio of total debt book value /total assets, earnings before interest, tax and depreciation/total assets ratio, ratio of retained earnings/total assets, natural logarithm of total assets, an export dummy variable, real GDP growth rate, propensity to issue out dividends, industry effects, dummy variable that accounts for the Greek debt crisis effect	30 886 privately-owned corporates	Multi-period logit model
Jacoby, Li and Liu (2019): 'Financial distress, political affiliation, and earnings management: the case of politically-affiliated private firms'	To examine the association between firm financial distress and earnings management and further, analyse the joint moderating influences of political connection and regional development on this association.	Ratio of working capital/total assets, retained earnings/total assets ratio, ratio of operating income/total assets, equity book value/total liabilities	292,223 private firm-year observations	Z(EM)-score, Ordinary Least Squares regression model
Range, Njeru and Waititu (2018): 'Using Altman's Z-score (sales/total assets) ratio model in assessing the likelihood of bankruptcy for sugar companies in Kenya'	To examine the influence of sales/total assets ratio on both privately-held and government-owned sugar corporations' bankruptcy forecasting in Kenya	Sales/total assets ratio	10 sugar firms, i.e., 6 government-owned and 4 private owned corporations	Altman's Z-score model, questionnaires
Takahashi, Taques and Basso (2018): 'Altman's	To assess the precision of the Altman (1983)'s	Earnings before interest and tax/total	622 private firms	Altman (1983) Z′-score model

bankruptcy prediction model: test on a wide out of business private companies sample'	Z′-score bankruptcy forecasting model applying an extensive privately-owned corporate sample	assets ratio, ratio of retained earnings/total assets, working capital/total assets ratio, ratio of equity book value / book value of total liabilities, ratio of sales/total assets		
Altman et al. (2017): 'Financial distress prediction in an international context: a review and empirical analysis of Altman's Z-score model'	To evaluate the forecasting capacity of the Altman (1983) Z″-score model using a massive international data set	Working capital/total assets ratio, ratio of retained earnings/total assets, ratio of earnings before interest and tax/total assets, ratio of equity book value/total liabilities book value, bankruptcy year, size of the corporate, corporate age, country of origin, company's industry	5 832 521 firms	Altman (1983) Z″-score model
Stojanovic and Drinic (2017): 'Applicability of Z-score models on the agricultural companies in the Republic of Srpska (Bosnia and Herzegovina)'	To examine the predictive ability of the Altman's Z-score models when implemented to agricultural firms in the Republic of Srpska	Ratio of retained earnings/ total assets, ratio of working capital/total assets, ratio of earnings before interest and tax/total assets, ratio of equity market value /total debt book value (Z-score), ratio of total equity/total liabilities (Z′-score and Z″-score models), sales/total assets ratio	270 agricultural firms i.e. 25 publicly-held, and 245 privately-traded firms	Z-score models (Z, Z′ and Z″)
Slefendorfas (2016): 'Bankruptcy prediction model for private limited companies of Lithuania'	To develop a bankruptcy forecasting model for privately-traded limited corporations in Lithuania	156 diverse financial ratios	145 small and medium private companies	Stepwise multivariate discriminant analysis
Charalambakis (2014): 'On corporate financial distress prediction: what can we learn from private firms in a small open economy?'	To analyse the predictor variables of financial distress for Greek privately-owned firms	Earnings before interest, tax and depreciation/total assets ratio, ratio of net sales/total assets, current liabilities/total assets ratio, ratio of retained earnings/total	30 934 private firms	Multi-period logit model

		assets, industry effects, dummy variable representing (current assets − current liabilities)/total assets, dummy variable if a corporate issues out dividends, dummy variable if a corporation exports, GDP growth, Greek debt crisis dummy variable		
Rim and Roy (2014): 'Classifying manufacturing firms in Lebanon: an application of Altman's model'	To assess whether the Z′-score model (Altman, 1983) can be implemented as a barometer for precisely categorising Lebanese private manufacturing firms	Ratio of retained earnings/total assets, ratio of working capital/total assets, earnings before interest and tax/total assets ratio, ratio of equity book value /total liabilities, ratio of sales/total assets	11 private companies	Z′-score model
Kpodoh (2009): 'Bankruptcy and financial distress prediction in the mobile telecom industry: the case of MTN-Ghana, Millicom-Ghana and Ghana Telecom'	To analyse the prediction capacity of the Altman's Z″-score model implementing a data matrix of mobile operators in Ghana	Retained earnings/total assets ratio, ratio of working capital/total assets, earnings before interest and tax/total assets ratio, ratio of net worth/total liabilities	3 private firms	Altman's Z″-score model, questionnaires
Eljelly and Mansour (2001): 'Predicting private companies failure in Sudan'	To predict private firm failure in Sudan	18 different financial ratios	60 private firms	Profile analysis, dichotomous classification technique, Altman's Z′-score model, stepwise multiple discriminant analysis

Although the incorporated studies were published between January 2000 and December 2020, only 1/12 was published before 2009. This indicates that private corporate bankruptcy forecasting has turned out to be a research discipline of significant interest after the occurrence of the recent 2007 – 2008 global economic and financial crisis. The 2007 – 2008 global crisis revealed the deficiencies in risk management exercises in financial credit markets and, specifically, in default prediction (see Tinoco and Wilson, 2013). Of the reviewed studies, 11/12 are peer-reviewed journal articles whilst the

remaining 1/12 is an academic dissertation. As far as the vocabulary applied to describe corporate failure is concerned, the terms ‘bankruptcy’ and ‘financial distress’ were extensively used in the reviewed studies. The Z-score models were used to analyse private firm bankruptcy in 8/12 of the reviewed studies, while the remaining 4/12 applied other models such as multi-period logit models, decision trees and artificial neural networks. Of the 12 studies reviewed, financial ratios only were implemented in forecasting bankruptcy in 9 cases and the remaining 3 cases included diverse combinations of financial ratios, firm and loan characteristics, industry variables and macroeconomic factors in forecasting bankruptcy. Sample sizes adopted by the reviewed studies vary from as little as 3 firms (see Kpodoh, 2009) to several millions of corporations (see Altman et al., 2017). Audited financial statements were examined in 4/12 cases and in the remaining 8/12 cases it is not clearly stated whether audited or unaudited statements or both were analysed. In 7/12 cases the authors collected financial data of interest from huge electronic databases such as ICAP and Capital IQ® databases, while the other 5/12 cases gathered financial data of interest from other sources such as banks and United States Securities and Exchange Commission. A narrative summary of the reviewed studies is given below.

Papana and Spyridou (2020) assessed the capability of the four techniques, namely, decision trees, discriminant analysis, logit regression and neural networks, in forecasting financial bankruptcy implementing a Greek data set. The sample data matrix comprises medium and small Greek privately-traded corporations. The data was pooled from the court of first instance database, which contains publicly obtainable information deduced from the Greek privately-held corporates’ financial statements. In their study (Papana and Spyridou, 2020), 50 accounting ratios were adopted. Time-varying predictor variables were lagged so as to proficiently forecast financial distress. In this study, a Greek privately-traded corporation is considered to be distressed financially if it has been: (i) confirmed as bankrupt or (ii) liquidated or dissolved or inactive and simultaneously its ordinary equity is below 50% of its share capital. The firms in the sample were congregated into two classes, i.e., bankrupt or non-bankrupt. Each bankrupt corporate was paired with a similar non-bankrupt corporate taking into account factors such as industry type and total assets volume. Financial data was gathered from the balance sheets of corporates and bankrupt corporations were analysed for the preceding 3 years of operation before bankruptcy. The corporations’ balance sheets adopted are from the observation period 2010 - 2012. For every year considered,

the sample data matrix comprised 100 non-bankrupt and 100 bankrupt paired Greek corporations. The study findings indicated that discriminant analysis is marginally superior to the other evaluated models.

Using a vast sample of 30 886 Greek privately-owned corporates with 188 065 yearly observations that operated over the observation period from 2003 to 2011, Charalambakis and Garrett (2019) analysed the drivers of financial distress probability for privately-traded corporates in Greece. The data was sourced from the database ICAP which comprises yearly freely accessible data for approximately 60 000 Greek privately-traded corporations primarily deduced from their financial records. This study omitted financial and state-owned corporates from the sample. To examine which drivers are correlated with the probability of financial distress for Greek privately-traded corporations, the study primarily focused on financial ratios deduced from the financial statements since market data is non-existent for private companies. Charalambakis and Garrett (2019) implemented a multi-period logit model and found that the leverage, the firm size, the retained earnings/total assets ratio, the profitability, the liquidity ratio, the growth rate of the real GDP, an export dummy variable and the tendency to declare dividends are all significant determinants of the financial distress probability for Greek privately-held companies. The authors suggested that a model encompassing these drivers is associated with the superior prediction ability. Further, the study observed that the model's forecasting capability remains great when the prediction time period is increased from 1 to 2 and 3 years, signifying that the technique performs well across short and elongated time periods.

Charalambakis and Garrett (2019) defined corporations that fall into financial distress and stated when this happens. The ICAP database adopted in this study ascertains the death year of the private company and the death type (i.e., liquidation, bankruptcy, idleness due to an insolvency condition, resolution, mergers and acquisitions). In their study, Charalambakis and Garrett (2019), a privately-owned corporation is regarded as distressed financially if it has been (a) affirmed liquidated, dissolved or bankrupt or (b) idle as a result of an insolvency condition. Corporations that have succeeded in resolving the insolvency condition or have been involved in mergers or acquisitions are considered non-bankrupt corporations. Implementing these conditions for categorising bankruptcy, Charalambakis and Garrett's (2019) final sample included 29 116 non-bankrupt corporations with 182 108 annual observations and 1 770 bankrupt corporates with 5 957 annual observations.

Implementing a sample data matrix of politically-connected privately-traded corporations in China, i.e., Chinese state-owned privately-held corporations whose financial reports are audited by autonomous auditors, Jacoby, Li and Liu (2019) assessed the relationship between management of earnings and firm financial distress. Jacoby, Li and Liu (2019) examined the financial distress of Chinese privately-traded corporations using the Z(EM)-score model (Altman, 2005). Altman's (2005) Z(EM)-score model was created to forecast financial distress for privately-held corporations in emerging markets. Further, the authors analysed the common moderating influences of political connection and regional development on the relationship between earnings management and firm financial distress using an Ordinary Least Squares regression model. The final sample adopted in this study has 292 223 corporate-year observations pooled over the observation period 1998 - 2009. The politically-connected privately-traded corporations' financial information was gathered from the China Non-listed Company Database, which offers comprehensive accounting data for politically-connected privately-held corporations and also, their place of operation. The results of their study (Jacoby, Li and Liu, 2019) proposed that financially distressed corporations are more involved in divulging little positive earnings as compared to financially healthy corporations. Moreover, it was discovered that political connection wanes the relationship between the management of small positive earnings and financial distress and the controlling influence of political connection is affected by regional development.

Implementing the Z-score model, Range, Njeru and Waititu (2018) examined the impact of the ratio of sales/total assets on forecasting bankruptcy for both Kenyan privately-held and government-owned sugar firms. A sample of 10 sugar corporations, i.e., 6 government-owned and 4 privately-traded firms, as per the 2016 Sugar Directorate yearbook, was analysed in their experiment. Questionnaires were employed to gather non-financial data for the government-owned sugar corporations. The Altman's Z-score model's five accounting ratios were deduced from the audited financial reports of the government-owned corporates collected over the sample period from 2007 to 2016. For privately-held sugar firms, data was gathered from the audited financial records for the observation period from 2011 to 2015. The data sets were gathered from the sugar firms directly, the firms' websites, the Commodity Fund and the Sugar Directorate. Range, Njeru and Waititu (2018) posited that the sales/total assets ratio has no considerable effect on the possibility of bankruptcy for Kenyan sugar firms.

Takahashi, Taques and Basso (2018) examined the precision of the Altman (1993) bankruptcy prediction model (Z′-score) using an extensive sample of 622 private firms that went bankrupt in the observation period spanning 29 years, that is, from 1985 to 2013. These sample firms were pooled from more than 10 developed and undeveloped North American economies and 9 diverse industries. The corporations were collected from Capital IQ® and were categorised by industries premised on the North America Industrial Classification and the economy of origin. Financial ratios adopted in the creation of the Z′-score model for private firms offered useful insights on the bankruptcy probability and solvency for private firms from the given data matrix. The Z′-score model indicated a forecasting precision of roughly 60% in this article.

Altman et al. (2017) evaluated the prediction ability of Altman (1968)'s Z-score model in forecasting bankruptcy and some kinds of corporate distress for corporates from 3 non-European and 31 European economies using diverse amendments of the original model. Besides the firms from the United States of America and China, the sample corporates were mainly privately-traded and comprised non-financial corporates across all economic sectors. Altman et al. (2017) adopted the original Altman's (1983) Z″-score model for privately-owned and publicly-traded manufacturing and non-manufacturing corporations. The principal inspiration for the formation of the Z″-score model was to design a technique that could be applied to firms in developing markets. In addition to the initial four accounting ratios for the Z″-score model, namely, the working capital/total assets, retained earnings/total assets, earnings before interest and tax/total assets and equity book value /total liabilities book value ratios, Altman et al. (2017) incorporated the firm size, the year of bankruptcy, the firm age, the country of origin and the firm industry in bankruptcy prediction. In their study, primary data was collected from the Bureau Van Dijk's databases, ORBIS, in which 99% of the firms are private corporations from several industries. The authors adopted a huge international data set of 5 832 521 failed and non-failed corporates pooled over the sample period from 2007 to 2010. The sample was split into an estimation sample containing 2 602 563 non-failed and 38 215 failed companies and a test sample composed of 43 664 failed and 3 148 079 non-failed corporates. Their study provides compelling evidence indicating that the general Z-score model could be applied sensibly well in most economies (with the forecasting accuracy of roughly 0.75) and its prediction ability could be enhanced to more than 0.90 by adopting economy-specific financial ratios and other additional factors.

ORBIS has five categories for active companies, which are, payment default, active, receivership, branch and dormant. ORBIS also has seven groups for inactive corporations that ceased to conduct business undertakings, i.e., dissolved, bankruptcy, dissolved-merger, branch, dissolved-demerger, no precision and in liquidation. Of these categories, 'active' only was nominated to denote corporates that are not distressed. In picking the failed corporates for most economies, Altman et al. (2017) considered corporations failed if their ORBIS status is indicated as being bankrupt or under receivership.

Stojanovic and Drinic (2017) examined the Z-score models' forecasting performance when applied to the Republic of Srpska's agricultural corporations. The authors compiled financial data from the formally submitted financial statements of 270 agricultural corporations for the period 2010 to 2015. Out of the 270 firms, 25 were publicly owned firms, while the rest were private manufacturing and non-manufacturing corporates. For publicly-held corporations, the study implemented all the 3 Z-score models (Z-score, Z′-score and Z″-score), while, for the rest of the corporates, the authors analysed the forecasting ability of the Z′-score and Z″-score models. Experimental results of this article indicated that the Z-score models are not dependable in bankruptcy forecasting and creditworthiness examination but can be valuable tools in recognising agricultural firms characterised by extended financial challenges, particularly if non-financial factors are incorporated.

Slefendorfas (2016) adopted a data matrix of 145 corporates, seventy-three of which were bankrupt and seventy-two were non-bankrupt. The financial data for firms was collected over the period 2007 – 2013. To develop a linear function Z_{GS}, the authors employed stepwise multivariate discriminant analysis. The financial information was gathered from the Credit Bureau "CreditInfo Lithuania" and 156 different financial ratios were adopted in designing the model. In the study, the empirical results indicated that 89% of the firms are precisely categorised. Slefendorfas (2016) propounded that the financial information for microsized corporations is susceptible to changes and could adversely influence model prediction ability. The authors also declared that big firms' financial information is insensitive to changes and huge corporations are characterised by low bankruptcy probability. Hence, the study designed a bankruptcy forecasting model for Lithuanian private firms using the financial data for small and medium-sized private corporations with at least 10 and at most 250 employees.

To examine which determinants influence the forecasting of private firm financial distress, Charalambakis (2014) adopted an enormous panel data set containing a sample of 30 934 Greek privately-traded firms with 188 364 yearly observations collected over the years 2003 to 2011. The sample was gathered from the ICAP database, which encompasses freely accessible information compiled mainly from the financial statements for approximately 60 000 Greek privately-owned corporates. In that study, financial institutions and utilities were omitted from the sample. Using a multi-period logit model or equivalently, a discrete hazard model, that includes the industry effects, the author identified six company-specific drivers that significantly explain the financial distress probability for Greek privately-owned corporations. The experimental results of the study showed that the leverage, the profitability, the ratio of retained earnings/total assets, the liquidity, the capacity of a corporate to export and the capability of a corporate to declare dividends are all robust drivers of private firm financial distress. Also, the article discovered that a dummy variable that accounts for the impact of the Greek debt crisis and the growth of GDP influence the financial distress likelihood. The study concluded that the multi-period logit model that includes six company-specific drivers, the industry dummies and the GDP growth displayed superior forecasting capacity. Further, the model's forecasting capability stayed high when the forecast period was increased.

Charalambakis (2014) defined which corporations fall into financial distress and when this happens. The ICAP database pinpoints the date of death and type of death of a privately-owned corporation such as liquidation, bankruptcy, inactivity, resolution, acquisitions, mergers, etc. Charalambakis (2014) regarded a Greek privately-traded corporate as financially distressed if it has been (i) bankrupt or (ii) dissolved or liquidated or inactive and simultaneously its ordinary equity is below 50% of the share capital. Premised on the above mentioned two conditions, the author categorised 1 772 companies with 5 965 yearly observations as bankrupt and 29 162 companies with 182 399 yearly observations as non-bankrupt.

In 2014, Rim and Roy (2014) examined whether the Z'-score model (Altman, 1983) could precisely categorise privately-traded Lebanese manufacturing corporations. Eleven privately-owned manufacturing firms were analysed over a sample period from 2009 to 2011. Over this three-year observation period, the authors analysed the audited financial statements of these private manufacturing corporations. The data adopted in their study was employed by the Lebanese banks to assess and grant loans to private

manufacturing firms. Therefore, the principal objective of the research work was to categorise a sample of Lebanese privately-owned manufacturing corporates premised on the computed score and compare the model classification to the bank classification. Rim and Roy (2014) discovered that the Z′-score model (Altman, 1983) could act as a benchmark for categorising privately-held manufacturing corporations within a similar industrial sector in Lebanon.

Adopting a sample data set of three major privately-traded mobile operators in Ghana (i.e., Mobile Telecommunications Network Ltd, Ghana Telecommunication Company Ltd and Millicom Ghana Ltd (Tigo)), Kpodoh (2009) assessed the prediction capacity of the Altman's Z″-score model. The research work intermingled quantitative analysis with corporate governance and managerial matters. Primary data was gathered using questionnaires and secondary data was compiled from yearly financial reports, reports of industry analysts and industry regulators. The Z″-scores of the sample firms were computed using financial ratios deduced from the financial records. Afterwards, the Z″-scores of the sample corporates were compared with the Z″-scores of the mobile operators that previously fell into bankruptcy in the same sector. Kpodoh (2009) collected the required data for the study from the Registrar General's Department, the National Communication Authority, the United States Security and Exchange Commission, the questionnaires administered to the sample firms, the journal papers and the reports of industry analysts. The study results established the predicting power and capacity of the Z″-score model in forecasting private firm failure since it projected precisely the financial distress situations of sample corporates.

Eljelly and Mansour (2001) implemented profile analysis and dichotomous classification methods to analyse the capability of univariate models in forecasting the failure of privately-held firms in Sudan, which was associated with a simple and unsophisticated economic environment. Later, the authors reproduced Altman's Z′-score model but discovered that its predictive performance is inferior to the Z′-score results attained in advanced and other undeveloped countries. The authors then re-calculated the parameters of the Z′-score model and established a substantial enhancement in its forecasting ability. Eventually, implementing stepwise multiple discriminant analysis, the study created a model with three factors that is superior to the replicated and re-estimated Z′-score models in classifying corporations into failed and non-failed categories. In this paper, a corporation was considered failed if it has been liquidated or reorganised or incapable of repaying its obligations in time. The private firm sample

was gathered over the observation period from 1970 to 1996. In the final sample, the authors adopted 30 failed privately-held corporations (i.e. 15 trading, 7 transport and 8 industrial) and 30 non-failed privately-traded firms. Sample corporates were selected randomly and their information was gathered from their audited financial reports. Conceptually, in the final sample, failed corporations were matched with non-failed corporates with roughly the same sizes of assets gathered from the same industrial sectors and years of the financial statements.

Given that the majority of the studies reviewed in this study are founded on the Z-score models introduced by Altman, the researcher see it fit to provide an overview of these Z-score models, that is, Z-score model (Altman, 1968), Z′-score model (Altman, 1983) and Z″-score model (Altman, 1983). Altman (1968) designed the original Z-score model applying a data matrix of sixty-six manufacturing firms, thirty-three of which were bankrupt (Group 1) and the other thirty-three were non-bankrupt (Group 2). These corporations were gathered over the sample period from 1946 to 1965. Firms in Group 2 were prudently nominated so that they match those in Group 1. However, the sizes of the assets of the corporations included in Groups 1 and 2 were not precisely matched by Altman (1968). Hence, Group 2 corporates were marginally bigger than companies in Group 1. Altman (1968) eliminated small companies because of data shortages and huge corporates since bankruptcy was uncommon among these corporates during that time. The financial data of the bankrupt corporates was deduced from financial statements collected one year before bankruptcy.

Altman (1968) assembled twenty-two imperative prospective accounting ratios deduced from the assessed financial reports. The candidate accounting ratios represented five standard risk factors: activity, liquidity, leverage, profitability and solvency. Altman (1968) proposed the discriminant function given by

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5,$$

where, Z = overall index, X_1 = ratio of working capital/total assets, X_2 = retained earnings/total assets ratio, X_3 = ratio of earnings before interest and tax/total assets, X_4 = equity market value /total liabilities book value ratio and X_5 = ratio of sales/total assets.

The Z-score model is relevant to only listed corporates since it is premised on the firms' market value (Altman, 1983). To design a privately-held firm bankruptcy prediction technique, Altman (1983) created the Z′-score model using data adopted by Altman

(1968) and in X_4, replaced the equity market value with the equity book value. The Z′-score model (Altman, 1983) is described by

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5,$$

where, X_4 = ratio of equity book value/total liabilities book value, while the other predictors remained unchanged as those in the initial Z-score model (Altman, 1968).

Altman (1983) failed to analyse the Z′-score model on a secondary data matrix because of data shortages for privately-owned corporations. Nevertheless, the author assessed the precision of the Z″-score model with four variables that omitted the ratio of sales/total assets, X_5, from the re-estimated model. The ratio of sales/total assets was omitted from the Z″-score model due to an industry influence that is more probable to occur when such a sector-sensitive predictor is incorporated (Altman et al., 2017). Altman's (1983) Z″-score model is given by

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4.$$

Basically, the Z″-score model was created for both privately-owned and publicly-traded manufacturing and non-manufacturing firms.

Further, since each domain has its own uniqueness mainly due to diverse bankruptcy laws, Altman (2005) examined the implementation of one of the Z-score family of models in emerging markets. Altman (2005) suggested an emerging market Z-score model, i.e., Z(EM)-score model, for corporate bonds in emerging markets. Basically, the Z(EM)-score model is an improved form of the initial Z-score model. The Z(EM)-score model can be implemented to non-manufacturing and manufacturing corporations and is applicable to privately-owned and publicly-traded corporations. Altman (2005) articulated that the Z(EM)-score model includes certain credit features of corporates in emerging markets and is appropriate for evaluating comparative value among credits in emerging markets. In particular, the basis of the Z(EM)-score model is an augmentation of the Z″-score model. The Z(EM)-score model is given by

$$\text{Z(EM)-score} = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4,$$

where, X_1 = ratio of working capital/total assets, X_2 = retained earnings/total assets ratio, X_3 = ratio of operating income/total assets, X_4 = equity book value /total liabilities and 3.25 is a constant term.

2.4 Results and discussion

The current scoping review results are presented and discussed in this section. Basically, the results are reported according to main outcome variables, that is, reasons and motives for research, emerging trends and the research gaps in private corporate bankruptcy risk forecasting in developing economies. The analysis of the outcome variables is supported by the available extensive literature from other sources. This discussion of the results aims to be as comprehensive as possible. The first part of this section outlines the reasons and motives for predicting private corporate bankruptcy risk in developing economies and the second part describes emerging trends in forecasting bankruptcy risk for private firms in undeveloped economies. Recent developments in developing countries that have been pushing for the designing of private firm bankruptcy forecasting techniques in such markets are also presented in the second part of this section. Lastly, the third part of this section reveals the research gaps in private corporate bankruptcy risk modelling in developing economies.

2.4.1 Reasons and motives for research

As noted in the reviewed studies, it is imperative to forecast bankruptcy for private firms in developing countries due to a number of reasons. At least 4 of the 12 reviewed studies highlighted that private corporates are the dominant legal forms of firms in developing economies (see Charalambakis and Garrett, 2019; Jacoby, Li and Liu, 2019; Slefendorfas, 2016; Charalambakis, 2014). Reviewed studies (Charalambakis and Garrett, 2019; Jacoby, Li and Liu, 2019; Charalambakis, 2014 and references therein) and other studies (Pertuz and Perez, 2021; Majukwa, 2019; Foghani, Mahadi and Omar, 2017; Hyder and Lussier, 2016; Chiwara, 2015; Organisation for Economic Co-operation and Development, 2015; Halabi and Lussier, 2014), indicated that private corporations promote economic growth and development, stimulate financial and technological innovations and reduce unemployment rates in developing economies. Further, a number of studies confirmed a positive impact of new firms, in general, on social, economic and environmental well-being (see, for example, Neumann, 2020 and references therein).

Despite the economic importance of the privately-traded firms, from this review (see, for instance, Papana and Spyridou, 2020; Charalambakis and Garrett, 2019; Charalambakis, 2014) it is revealed that corporate bankruptcy forecasting literature is largely devoted to publicly-held corporates in developed economies for which data is

extensively available, while little is known about the bankruptcy probability drivers for private corporations. Charalambakis and Garrett (2019) and Charalambakis (2014) argued that very little is well-known about the drivers of financial distress probability for privately-traded corporations in undeveloped countries. Some studies (see, for example, Falkenstein, Boral and Carty, 2000) revealed that bankruptcy forecasting models premised on data collected from publicly-traded corporations and applied to privately-owned firms will likely distort real default risk since private companies are unlike public firms. Compared to publicly-held companies, privately-traded firms are exposed to different regulatory and environmental factors. Reviewed studies (see, for example, Altman et al., 2017) and other studies (Faccio et al., 2012; Michaely and Roberts, 2012; Gao, Hartford and Li, 2012; Asker, Farre-Mensa and Ljungqvist, 2012) articulated that compared to public corporations, private corporates are smaller in size, use more leverage, depend more on bank loans and trade credit, invest more and are usually associated with raised costs of borrowing. Therefore, the correlation between accounting ratios and bankruptcy risk varies considerably across public and private firms (Falkenstein, Boral and Carty, 2000).

Further, Slefendorfas (2016) propounded that financial ratios compiled from the financial statements of corporations of different sizes cannot be compared because the prediction results may be biased. Of the reviewed studies, Altman et al. (2017) and Slefendorfas (2016), and other studies, such as Balcaen and Ooghe (2006) and Altman (1968), clearly indicated that financial information for small firms is susceptible to changes, thereby affecting the forecasting power of the designed models. By contrast, Altman et al. (2017), Slefendorfas (2016) and Altman (1968) noted that financial information for large corporates is insensitive to changes and huge corporates are associated with low bankruptcies. This indicates that small and big corporations should not be included in the same samples when creating reliable bankruptcy probability models for privately-owned firms. Using the same line of reasoning, Charalambakis and Garett (2019) and Charalambakis (2014) indicated that the covariates for bankruptcy probability for small and medium private corporations are not the same. Thus, data sets of privately-owned firms should be designed based on firm asset size when forecasting bankruptcy. Since private corporations are smaller than public corporates, it is necessary to design dependable bankruptcy forecasting models specifically for privately-owned firms (Charalambakis and Garrett, 2019). Charalambakis and Garrett (2019) also

postulated that these bankruptcy forecasting models help financial institutions design policies linked to the provision and cost of credit to private corporations.

Of the reviewed studies, Eljelly and Mansour (2001) suggested that undeveloped economies are characterised by unique economic characteristics. Papana and Spyridou, (2020) and Eljelly and Mansour (2001) indicated that simple models for predicting corporate failure, such as multiple discriminant analysis, can do a greater job in unsophisticated developing country economic atmospheres than complex corporate failure prediction models developed in advanced countries. Moreover, some studies, such as Obradovic et al. (2018), Waqas and Md-Rus (2018), Liang, Tsai and Wu (2015) and Fedorova, Gilenko and Dovzhenko (2013), highlighted that it is not easy to implement corporate default risk models created for developed countries in developing economies because these countries are dissimilar. Developing economies are usually associated with weak institutional structures such as nonexistence of rule of law and deficiency of property rights which directly affect how corporations deal with financial distress. Waqas and Md-Rus (2018) suggested that it is essential to appreciate that advanced economies have diversified economic configurations and clearly stated bankruptcy laws and procedures, while undeveloped markets are deficient of such diversified economic configurations and bankruptcy laws and procedures. Further, Senbet and Wang (2012) indicated that several developing countries have no effective reorganisation processes for distressed yet viable corporations and the costs of implementing the bankruptcy processes to solve financial distress challenges are exorbitant with regards to time and other resources. Weak institutional structures and undiversified economic configurations in developing economies affect how corporate bankruptcy is forecasted. Compared to advanced countries, developing economies are hard hit by downturn conditions due to their economic structures, thereby exposing more firms from developing markets to bankruptcy risk (Obradovic et al., 2018). Therefore, Rylov, Shkurkin and Borisova (2016) and Slefendorfas (2016) propounded that applying corporate bankruptcy modelling techniques based on foreign data from advanced markets to developing economies does not always produce credible results because these models do not reflect the institutional, economic and financial features of developing economies.

Although from a regulatory standpoint international financial institutions require to create international bankruptcy models that can be implemented in their branches and

subsidiaries to regulate risk through the entire banking groups (Altman et al., 2017), it is well documented that each developing country has its unique characteristics such as financial and economic conditions, accounting legislation and practices, bankruptcy processes, taxes, debtor rights and creditor rights and how those rights are exercised, and investor protection, which affect how bankruptcy probability is analysed (Altman, 2018; Altman et al., 2017; Slefendorfas, 2016; Rim and Roy, 2014; Geiger, Raghunandan and Rama, 2005). This shows that developing countries are not completely the same, they vary a good deal from each other. In particular, procedures of bankruptcy differ significantly across developing economies on issues such as creditor rights and control in the process of bankruptcy (see, for instance, Senbet and Wang, 2012). Thus, formal bankruptcy proceedings vary across developing markets. As a result, expected and unexpected default loss functions, and firm exit, survival and restructuring are influenced in a number of different dimensions (Altman, Resti and Sironi, 2005). These differences partially emanate from the variances in legal origins of economies, which impact the law enforcement and legal rules. Davydenko and Franks (2008) highlighted that huge dissimilarities in the rights of creditors across economies incentivise financial institutions to alter their reorganisation and lending exercises in order to alleviate costly facets of the law of bankruptcy. Therefore, Slefendorfas (2016) articulated that although some bankruptcy models are implemented the world over, researchers continuously attempt to create novel models that can be implemented to firms functioning in specific economies in search of superior models. Reviewed studies (Takahashi, Taques and Basso, 2018; Altman et al., 2017 and Slefendorfas, 2016) and other studies (see, for instance, Altman, 2018) showed that bankruptcy detection models built using economy-specific data are characterised by high forecasting ability.

Reviewed studies (Papana and Spyridou, 2020; Takahashi, Taques and Basso, 2018; Altman et al., 2017; Slefendorfas, 2016) suggested that the relationship between private firm bankruptcy risk and its determinants changes as, among other things, periods of time, technology, accounting methods, corporate strategies, economic conditions and financial situations change. Slefendorf as (2016) posited that prevalent and universally implemented bankruptcy forecasting models do not indicate shifts in today's economic conditions, country differences and competition changes and the primary inputs (especially financial information) of such techniques are outdated. The author further proffered that many such models were designed on dissimilar firms. Changes in the relationship between corporate bankruptcy risk and its determinants lead to data

instability or non-stationarity problems, leading to reduced forecasting capacity and instability of the created models over time (Papana and Spyridou, 2020; Takahashi, Taques and Basso, 2018). Takahashi, Taques and Basso (2018), Brindescu-Olariu (2016), Singh and Mishra (2016), Smaranda (2014) and Timmermans (2014) showed that corporate bankruptcy detection models need to be frequently revalidated and recalibrated in direct response to changes in circumstances. Further, Singh and Mishra (2016), Timmermans, (2014), Hayden (2011), Eljelly and Mansour (2001) and Grice and Dugan (2001) highlighted that re-designing of bankruptcy models (especially using the most recent data) promises that the forecasting ability of the models does not decline. In support of this, another study, Avenhuis (2013), averred that re-designing a model with specific and larger sample produces superior forecasting ability.

2.4.2 Emerging trends

Even though the studies reviewed did not indicate the developments in the recent borrowing spree in developing economies, one study, Atradius Economic Research (2016), noted that these developments can be divided into seven:

- Firm balance sheets have been progressively leveraged.
- The share of external financing to corporates in emerging markets has not changed. On average, corporations in developing in developing economies generally finance themselves using mainly local currencies from local banks in domestic markets.
- External debt has significantly broadened. In some instances, external debt has outstripped the increase in external receipts, exposing firms in developing economies to exchange rate and refinancing risk.
- Intercompany debt has amplified. Corporations in developing countries have considerably augmented their exterior borrowing, using especially bonds issued by their subsidiaries overseas.
- The accumulation of external debt frequently intermediated through the domestic banking system is rampant in the non-tradables industries such as local property industries.
- Weaker world commodity prices have considerably condensed the exporting corporations' natural hedge.
- In aggregate, corporates in developing economies have become less profitable, predominantly due to the drop in prices of commodities and the global trade weakening.

Generally, these developments show that developing economies are associated with unique features which have significant impact on the bankruptcy risk for privately-traded corporations and are not a favourable environment for credit risk. For instance, high levels of leverage and low profitability levels expose firms in developing countries to both endogenous and exogenous liquidity shocks which raise the probability of bankruptcy. For more expositions on the developments in the most current borrowing splurge in developing economies, the interested reader is referred to Cortina, Didier and Schmukler (2018), Alfaro et al. (2017), International Monetary Fund (2015) and Bank for International Settlements (2014), among other sources.

As noted in the reviewed studies (Papana and Spyridou; 2020; Charalambakis and Garrett, 2019; Charalambakis, 2014; Eljelly and Mansour, 2001), the creation of bankruptcy forecasting models for private corporations in developing countries is a challenging task because of the scarcity of default data and information for private corporations. Limited default data and information for privately-traded corporates is predominantly credited to the fact that in most developing countries, private firms are not mandated to publicise their financial statements. Rylov, Shkurkin and Borisova (2016) indicated that corporate bankruptcy forecasting literature is limited in developing economies since they are characterised by limited historical statistical data, closed markets, institutional and legal barriers and reduced predictive power of market signals. Thus, there is lack of dependable databases for private corporate default data and information. However, of late, as noted in reviewed studies (Papana and Spyridou, 2020; Charalambakis and Garrett, 2019; Takahashi, Taques and Basso, 2018; Altman et al., 2017; Slefendorfas, 2016; Charalabakis, 2014), it has emerged that slightly more effort has been put in private firm bankruptcy detection following the significant expansion of private firm loan business, occurrence of the 2007 – 2008 global crisis, the increase in the availability of massive databases for private firm default data and information such as ICAP, ORBIS and Capital IQ® databases, the evolution of statistical techniques that promote dynamic modelling of credit risk and the introduction of Basel II/III principles.

Further review of the literature discovers that even though in several countries private firms are not obligated by rules and regulations to produce audited financial statements and records, some private corporates do (see Range, Njeru and Waititu, 2018; Rim and Roy, 2014; Eljelly and Mansour, 2001). Thus, in some instances, private firm

bankruptcy risk is analysed using audited financial statements. Audited financial reports promise that there are no substantial misstatements or mistakes in the reported results (Bratten et al., 2013; Minnis, 2011). Bratten et al. (2013) and Dechow, Ge and Schrand (2010) proffered the argument that by plummeting the misrepresentations of financial reports, a reliable audit warranties dependable financial reporting. Moreover, to guarantee or augment the audit services' quality in order to re-establish public confidence in the audit function, the audit market is exposed to continuing regulations, e.g., the 8th Directive in the European Union and the Sarbanes Oxley Act in the United States (see Widmann, Follert and Matthias Wolz, 2020, Pott, Mock and Watrin, 2009 and references therein). The link between audited financial statements and the bankruptcy risk for privately-traded corporations has not been clearly dealt with by the reviewed studies, hence the existent extensive literature is used to debate it. Several authors proposed that private firms with audited financial reports are characterised by lower bankruptcy risks than their unaudited counterparts in the eyes of the providers of finance (Cenciarelli, Greco and Allegrin, 2018; Hamzani and Achmad, 2018; Gul, Zhou and Zhu, 2013; Jahur and Quadir, 2012; Blackwell, Noland and Winters, 1998). Cenciarelli, Greco and Allegrin (2018) suggested that huge auditing companies reduce the likelihood of bankruptcy risk because they have the resources, skills and knowledge about a particular sector and its firms and can assess internal control systems of a firm, gauge its earnings against the sector average and efficiently examine discount rates and cash flow estimates. Rim and Roy (2014) indicated that, of late, some financial institutions have been demanding audited financial statements from the private firms before granting them loans.

As noted in almost all of the reviewed studies, several bankruptcy prediction models for privately-held corporates in developing markets are based on accounting ratios. Nevertheless, although reviewed studies did not look on the comparative forecasting ability of these accounting-based bankruptcy models, some studies highlighted that the predictive capacity of standard accounting-based bankruptcy detection models has been declining over the years (Beaver, Correia and McNichols, 2012; Beaver, McNichols and Rhie, 2005). Further, trust in the practices of auditing and firm reporting has swiftly dwindled of late due to numerous significant accounting scandals in both developed and developing economies (see, for instance, Widmann, Follert and Matthias Wolz, 2020, Pott, Mock and Watrin, 2009 and references therein). Hence, some studies such as Beaver, Correia and McNichols (2012) and Agarwal and Taffler (2008) proposed that

supplementary predictor variables need to be incorporated into the bankruptcy forecasting models. From the reviewed studies (Charalambakis and Garrett, 2019; Altman et al., 2017; Charalambakis, 2014), it has been observed that, over the recent years, the predictive capacity of private firm bankruptcy models has been being enhanced by combining financial ratios with firm and loan characteristics, industry effects and macroeconomic variables as the predictor variables. Moreover, reviewed studies (Charalambakis and Garett, 2019; Takahashi, Taques and Basso, 2018; Charalambakis, 2014) posited that to determine private firm bankruptcy probability under downturn conditions accurately, macroeconomic conditions usually captured by macroeconomic variables must be incorporated into the models. This issue is supported by other studies such as Canals-Cerda and Kerr (2015a, 2015b). Takahashi, Taques and Basso (2018) proposed that bankruptcy models that take into account periods with economic crises and times characterised by greater stability may produce highly representative results as far as bankruptcy probability is concerned. Captivatingly, since the outburst of the 2007 – 2008 universal financial and economic crisis, the forecasting of bankruptcy probability for privately-traded corporations under downturn conditions has been receiving a lot of scientific and academic research attention.

Moreover, Gupta, Gregoriou and Healy (2015) and Altman, Sabato and Wilson (2010) revealed that non-financial variables enhance the forecasting power of bankruptcy prediction models. Altman (2018) suggested that to instantly take into account shifts in the creditworthiness of corporate and individual borrowers, most recent breakthroughs in financial technology attempt to investigate the application of non-traditional measures and big data such as payable history, analysis of invoices and governance characteristics; “clicks” on adverse information episodes and data; and inputs from the social media.

2.4.3 Research gaps

After highlighting the reasons and motives for research and emerging trends in forecasting bankruptcy probability for privately-traded firms in developing markets, as well as recent developments in developing countries that have been pushing for the creation of private firm bankruptcy prediction techniques in such markets, the study now moves on to identify the research gaps in the current literature. The identification of research gaps in this study depends on the reviewed articles and other supporting studies within the field of interest. Research gaps identified in the evidence could be

used to direct future research efforts in the area of private firm bankruptcy probability forecasting. Arksey and O'Malley (2005) argued that the idea of finding research gaps in the extant evidence base is imperative, and may or may not lead to a complete systematic review. In business and management literature, Clark et al. (2021) and Fisch and Block (2018) presented fundamental guidelines for conducting a systematic review.

It has been observed that privately-traded and publicly-held corporations are dissimilar and are affected by different regulatory and environmental factors. Also, it is well documented that developing markets are associated with unique institutional, regulatory, financial and economic conditions. Further, developing countries are not completely similar. These highlighted issues have consequences for bankruptcy prediction models. Henceforth, this study recommends creating country-specific models that predict bankruptcy probability for private firms specifically in developing countries. In partial support of this, Tinoco and Wilson (2013) posited that banks need to create default probability models which are specific to corporate sub-classes such as private corporations, SMEs and public corporates.

Several terms, such as 'failure', 'bankruptcy', 'insolvency', 'default' and 'liquidation', are usually applied interchangeably to refer to firm failure (see, for instance, Kpodoh, 2009). Papana and Spyridou (2020), Charalambakis and Garrett (2019), Altman, et al. (2017) and Charalambakis (2014) indicated that classifying private corporations into failed and non-failed corporates is conditional on the definition of 'corporate failure' adopted by the study since definitions of corporate failure are not homogeneous across countries. Using the same line of reasoning, Altman et al. (2017) highlighted that the definition of corporation failure hinges on the economy the corporate failure detection model is designed in and the conforming legislature regarding firm failure. This shows that there is no steady corporate failure definition in the financial credit markets. Not surprisingly, it has been revealed that the measures of corporate failure are selected subjectively in real-life. Further, it is worth noting that the corporation failure definition adopted impacts the choice of covariates for the bankruptcy probability for private corporations. Therefore, when comparing various unique studies generated from several countries, it is vital to consider the definitions of corporate failure adopted, and when designing bankruptcy forecasting models for private corporations in emerging markets, the applied definition of corporate failure should be clearly stated (see, for instance, Papana and Spyridou, 2020). This is imperative since uncareful and subjective

evaluation of the definition of corporate failure might generate biased results. In practice, there is a crucial requirement to create explicit private firm model/s of bankruptcy for each type of corporate failure in developing economies.

Given that private firms' stocks are not publicly-traded, that is, are not traded on stock exchanges, the primary source of private firm bankruptcy information and data are financial statements. Financial ratios that are used in the designing of private firm bankruptcy forecasting models are compiled from these financial statements. It has been observed that comparative ratios are customarily incorporated into the majority of private firm bankruptcy detection models. However, another study (Hayden, 2011), pronounced that dynamic ratios, e.g., total liabilities/total liabilities last year ratio, are also vital in forecasting corporate probability of bankruptcy. Dynamic ratios relate current to past levels of specific balance sheet entries. Since the examination of the forecasting ability of bankruptcy models for privately-traded corporations provides insights into the capability of financial ratios to detect bankruptcy, this study recommends the inclusion of both comparative and dynamic financial ratios when designing private corporate bankruptcy probability prediction models for developing economies. Moreover, since private corporations with audited financial reports are characterised by lower bankruptcy risk than their unaudited counterparts in the eyes of the providers of finance, it is vital to independently create bankruptcy forecasting models for audited and unaudited privately-held companies in developing economies from a credit risk management viewpoint.

There is ample evidence that indicates that the predictive capacity of private firm bankruptcy models is enhanced by combining financial ratios with non-financial variables, such as firm and loan features and macroeconomic factors, where data exists. The incorporation of only accounting ratios into bankruptcy failure forecasting models clearly assumes that all appropriate bankruptcy indicators (external and internal) are reflected in the financial statements (see Balcaen and Ooghe, 2004). However, financial reports do not embrace all appropriate information required to forecast corporate bankruptcy. Hence, from an ideological standpoint, in order to develop practically acceptable and precise models, it is recommended to generate bankruptcy forecasting models for private firms in developing countries that incorporate financial ratios, firm and loan characteristics and macroeconomic variables since they all encompass valuable information concerning the bankruptcy probability of private firms. Financial ratios,

firm and loan characteristics and macroeconomic variables complement each other. Hence, an inclusive model that incorporates these covariates seems to be the best alternative.

The inclusion of macroeconomic factors is attractive since they increase the timeliness and power of bankruptcy forecasting models. It is well documented that ignoring macroeconomic variables which capture macroeconomic conditions leads to imprecise estimates of bankruptcy probability especially when modelling bankruptcy risk under downturn conditions. However, there is an absence of well-defined estimation procedures and industry consensus on how to incorporate economic downturn conditions in private firm bankruptcy risk models, which has resulted in the introduction of diverse bankruptcy prediction models in the financial markets. Also, there is no consensus on which determinants have the most significant impact on private firm bankruptcy risk in the context of downturn conditions. Consequently, it is recommended that private firm bankruptcy prediction models that, in addition to accounting ratios and firm and loan features, incorporate macroeconomic variables and cover the whole business cycle should be created in developing countries.

Moreover, reviewed papers (Slefendorfas, 2016; Rim and Roy, 2014) and other studies (see Singh and Mishra, 2016) clearly indicated that bankruptcy probability prediction models for private corporates that include industry effects are associated with superior forecasting ability. Charalambakis (2014) discovered that a multi-period logit model that incorporates six company-specific drivers, the industry dummies and the GDP growth displayed superior forecasting capacity. In 2004, Chava and Jarrow (2004) augmented Shumway's (2001) discrete hazard model emphasising the significance of incorporating industry effects. Takahashi, Taques and Basso (2018) postulated that economic sectors are characterised by diverse intrinsic features and economies have unique economic structures that influence firms' performance in different industries in different dimensions. For instance, some industries are hit harder by downturn conditions than others, thereby exposing more firms from those industries hit harder by downturn conditions to more bankruptcy risks. This study recommends the creation of industry-specific bankruptcy detection techniques for private corporations in a particular developing country and the designing of country-specific bankruptcy probability prediction models for private corporates in undeveloped markets that include industry effects. In support of this, Tinoco and Wilson (2013) noted that for banks to create

effective corporate credit risk models they need to design default probability models which are specific to firm sub-categories such as private corporates, SMEs, public corporations and industry-specific default models, adjusted to variations in the macroeconomic conditions and altered to the accessibility and timeliness of data. In addition, to instantly take into account shifts in the creditworthiness of private firm borrowers, big data and non-traditional measures such as history of payables, analysis of invoices and governance characteristics; "clicks" on adverse information episodes and data; and inputs from the social media also need to be considered when forecasting private firm bankruptcy probability in developing countries (see, for example, Altman, 2018).

Reviewed literature offers sufficient evidence showing that there is no specific criterion for picking up the required predictor variables in the private firm bankruptcy forecasting domain, and various models apply diverse variables (see, for instance, Slefendorfas, 2016 and Eljelly and Mansour 2001). Lack of a reliable theoretical framework for selecting the required predictors in private corporate bankruptcy prediction may be attributed to limited research in this area. An economic theory to guide the selection of variables when building bankruptcy prediction models for private firms in developing countries is needed in order to generate dependable results. Since there is no credible theoretical framework that can be implemented to permit dependable picking of predictor variables, predictors are subjectively chosen in the literature. Bankruptcy probability variables are subjectively selected basing on their projecting ability and popularity in previous studies such as Altman (1983, 1968). However, it needs to be emphasised that choosing bankruptcy predictors premising on their popularity may not produce credible results since, for instance, prevalent financial ratios can be window dressed. Further, there is no consensus among authors on which covariates are the best indicators of private firm failure in developing economies. Therefore, selecting the initial set of variables based on statistical contemplations or a theoretical framework, or both, is necessary when developing bankruptcy models for private corporations in undeveloped economies.

Studies reviewed indicate that multiple discriminant analysis is one of the most used techniques in private firm bankruptcy prediction in undeveloped markets. In particular, the mainstream of the reviewed research articles is premised on the Altman's Z-score group of models (see Jacoby, Li and Liu, 2019; Range, Njeru and Waititu, 2018;

Stojanovic and Drinic, 2017; Rim and Roy, 2014; Eljelly and Mansour, 2001; Kpodoh, 2009). However, although the Z-score models have proved to be remarkably resilient over the years (see, for instance, Altman, 2018), there is abundant evidence that shows that, in some instances, the Z-score models are associated with low classification rates and are outclassed by other rival models in bankruptcy forecasting for private corporations in developing economies (see, for example, Eljelly and Mansour, 2001). This is partly attributed to the fact that, compared with the modern-day extremely sophisticated and multifaceted financial credit markets, when the original Z-score model was designed in 1968 credit markets were simpler. Therefore, the Z-score models need to be frequently revalidated and recalibrated in direct response to changes in circumstances to guarantee that their forecasting ability does not decline. In the same vein, bankruptcy prediction models for private corporations in developing economies should be re-designed with specific and larger samples in order to get superior forecasting ability. In addition, it may be imperative to implement more complex models which are widely used in advanced economies, such as hazard models and artificial neural networks, in private firm bankruptcy prediction in undeveloped markets to improve model forecasting abilities.

Moreover, Altman's Z-score models are static (single-period) models (Stojanovic and Drinic, 2017). They disregard the element that the bankruptcy likelihood does change over time since corporates transform as time moves on. Shumway (2001) articulated that predicting bankruptcy using static techniques results in unreliable and biased predictions of the likelihood of bankruptcy and inappropriate drivers' statistical significance inferences. Thus, in reality, there is a great need to detect bankruptcy probability for private corporates in developing markets using dynamic models that reflect the point that corporates transform over time and explicitly offer the anticipated time to failure. Dynamic models permit bankruptcy probability to vary over time horizons as a function of covariates that change with time periods as well. That is to say, dynamic models incorporate data indicating variations in the macroeconomic conditions, non-financial variables and other time variant predictors (see, for instance, Tinoco and Wilson, 2013). Also, dynamic models incorporating macroeconomic factors are imperative in stress testing default probability forecasts across credit portfolios.

2.5 Conclusions

The majority of studies on corporate bankruptcy detection are devoted to publicly-traded firms in advanced economies. Literature on bankruptcy prediction for private corporations is generally restricted and that for such corporates in undeveloped markets is even more restricted. Existent evidence on privately-owned corporate bankruptcy is substantially dedicated to advanced countries. Applying a scoping review structure of Arksey and O'Malley (2005), this chapter conducted a review of literature concerning bankruptcy forecasting for privately-held firms in undeveloped economies. The central purpose of this scoping review was to examine the reasons and motives for research, the emerging trends and research gaps in modelling bankruptcy risk for private corporations in developing countries. The results of this scoping review show that the estimation of bankruptcy probability for privately-traded corporations in developing economies is a relevant discipline that has not been appropriately examined and has some unique and unexplored areas due to its sophistication, and the distinctive business ethos of private corporates.

For future research, scoping reviews can be conducted to disclose how common and promising models perform in bankruptcy forecasting for privately-owned corporates in developing economies using specific criteria. There is likelihood that the scoping review may have overlooked some appropriate articles. This omission may be attributed to the selection of databases, time restrictions, elimination of the gray literature from the review, i.e., literature not published, and the exclusion of articles published in other languages other than English. Therefore, this study could be extended by adopting and reviewing a huge number of research articles over a long period of time to better understand bankruptcy probability prediction for privately-traded firms in developing economies. Additional research articles could be identified through searching in other databases, inclusion of gray literature and incorporation of studies published in other languages other than English. This current scoping review provided sufficient evidence to justify the undertaking of a full systematic review in this area of study.

Several gaps revealed in this current chapter are explored in chapters three and four. In chapter three, the research project suggests stepwise logistic regression models founded on diverse amalgamations of loan and firm features, financial ratios and macroeconomic factors, and applies the stepwise selection of some threshold criteria to forecast default for Zimbabwean privately-owned non-financial corporations under downturn conditions twelve months before default. Further, since it was revealed that audited and unaudited

private firms are not the same, chapter four creates stepwise logistic regression models premised on different mixtures of loan and firm features, financial ratios and macroeconomic factors to separately analyse the predictor variables of default probability for audited and unaudited Zimbabwean privately-held non-financial corporations under economic and financial stress twelve months prior to default.

Chapter 3: Corporate default risk modelling under distressed economic and financial conditions in a developing economy

(*This chapter has been published in the Journal of Credit Risk (see Appendix A3.1)*)

3.1 Introduction

In developing countries, financial institutions often struggle to develop the formal credit evaluation procedures that are widely used in advanced economies. Challenges include data scarcity, imperfect and shallow financial markets, insufficient technical capacity and lack of extensive penetration by both local and external rating firms (see, for example, Ozili, 2019). Not surprisingly, the use of data-intensive dynamic default forecasting models in its infancy in several developing economies due to limited data. Dynamic default prediction models emphasise the importance of duration effects.

The bulk of research has focused on the default detection models for public firms in developed economies due to the wider availability of reliable and comprehensive data (see, for instance, Charalambakis; Garrett, 2016 and Shumway, 2001). Research work on the drivers of default probability for privately-held companies is generally limited, and that for such companies in developing economies is even more limited. The literature on private firm default prediction modelling is chiefly focused on developed nations (see, for instance, Bauweraerts, 2016; Falkenstein, Boral and Carty, 2000). However, it has emerged that applying models constructed for developed economies to emerging markets does not always lead to granting of appropriate credit (Ashraf, Felix and Serrasqueiro, 2019; Rylov, Shkurkin and Borisova, 2016), because the economic structures of these countries are significantly different (Rylov, Shkurkin and Borisova, 2016; Fedorova, Gilenko and Dovzhenko, 2013). In the same vein, Altman (2018), Takahashi, Taques and Basso (2018) and Slefendorfas (2016) indicated that each economy has its unique features, and thus models developed specifically for individual countries outperform universal models.

The study contributes to the discourse of default risk modelling by analysing the drivers of default probability for private firms under distressed economic and financial conditions in a developing economy (Zimbabwe). Credit default prediction for private firms in developing economies is crucial for a number of reasons and has acted as motivation for several academic research papers (see, for example, Charalambakis and Garrett, 2019; Slefendorfas, 2016; Charalambakis, 2014). Private corporations are dominant firms in developing economies (Charalambakis and Garrett, 2019;

Slefendorfas, 2016; Organisation for Economic Co-operation and Development, 2015; Charalambakis, 2014), perhaps because developing economies are associated with underdeveloped local equity markets, which limits the use of price-based information (such as distance to default) in default prediction. Also, private firms promote economic growth and development and financial and technological innovations, and they reduce unemployment rates (Charalambakis and Garrett, 2019; Hyder and Lussier, 2016; Majoni, Matunhu and Chaderopa, 2016; Chiwara, 2015; Organisation for Economic Co-operation and Development, 2015; Halabi and Lussier, 2014; Wymenga et al., 2012). Given firms' economic contribution, Bauweraerts (2016) and Eckbo, Thorburn and Wang (2014) announced that their failure is associated with high social and economic costs.

Privately-traded corporates are unlike publicly owned companies; they are smaller in size, use more leverage, depend more on bank loans and trade credit, invest more and are associated with high costs of borrowing (Asker, Farre-Mensa and Ljungqvist, 2012; Gao, Hartford and Li, 2012; Michaely and Roberts, 2012). Charalambakis and Garrett (2019) reported that the non-stock-market variables that drive default probability for private and public firms are not the same. In the same vein, Falkenstein, Boral and Carty (2000) observed that the correlation between default risk and financial variables varies considerably across listed and private corporates. Moreover, public and private firms are affected by different regulatory and environmental variables. Falkenstein, Boral and Carty (2000) suggested that the importance of this observation is that default prediction techniques based on data gathered from public firms and applied to private corporates will likely distort real default risk.

Gathering default information and data for private firms is challenging since their stocks are not bought and sold on stock exchanges (Charalambakis and Garrett, 2019). This indicates that the records and financial statements of corporate borrowers accessed from banks are the primary sources of default data and information for private companies. Therefore, predicting the probability of default for private firms is vital because it helps banks generate policies related to the supply of credit to and the cost of credit to private firms (Charalambakis and Garrett, 2019). Moreover, evidence on the predictive performance of private firm default prediction models sheds more light on the capability of financial ratios to predict firm default.

The default probability is influenced by general macroeconomic conditions. Obradovic et al. (2018) and Canals-Cerda and Kerr (2015a) revealed that economic downturns are

associated with high default frequencies. Several authors (see, for example, Charalambakis and Garrett, 2019) have suggested that the inclusion of macroeconomic factors improves the forecasting results of private firm default prediction models. However, the dilemma is that there is lack of industry consensus on which macroeconomic factors have the most substantial impact on private firm default risk under downturn conditions, resulting in the introduction of diverse probability of default prediction methodologies.

This study proposes stepwise logistic regression models based on diverse combinations of loan and firm characteristics, financial ratios and macroeconomic factors, and uses the stepwise selection of some threshold criteria to predict default for Zimbabwean privately-owned non-financial firms under downturn conditions twelve months in advance. The study focuses on a twelve-month period because it permits financial institutions to take corrective action to avoid forecasted defaults and ensures that timely data is incorporated into the rating techniques (Hayden 2011; Basel Committee on Banking Supervision 1999). The primary focus of this analysis is on the economic interpretation of the estimated coefficients for the predictor variables incorporated into the designed models. To fit the models, the study adopts a unique cross-sectional data set of defaulted and non-defaulted private firm loan accounts accessed from an anonymised major Zimbabwean commercial bank over the observation period from 2010 to 2018. Geographically, the data set is an accurate representation of the Zimbabwean market.

Zimbabwe provides an exciting and challenging case in analysing default risk for private firms in developing countries. Over the past two decades Zimbabwe has experienced severe and prolonged distressed economic and financial conditions that have contributed to substantial deindustrialisation and informalisation of the economy. In order to stabilise the economy, the country phased out the Zimbabwean dollar in 2009 and adopted a basket of currencies that included the euro, South African rand, British pound, Botswana pula, and United States (US) dollar. However, the US dollar emerged as the presentation and functional currency of firms. Masiyandima et al. (2018) posited that the emergence of the US dollar as the main currency resulted in negative and low rates of inflation, which negatively impacted the country's growth. The economy witnessed 28 successive months of deflation from October 2014 to January 2017 (Masiyandima et al., 2018). World Bank Group (2020a) indicated that the real

gross domestic product (GDP) growth rate fell from more than 10% per year in 2010 - 2012 to an average of 2.5% between 2013 and 2018, while public debt and budget balance were on average 43.68% of GDP and -4.07% of GDP, respectively, during the observation period. The downturn conditions witnessed in Zimbabwe are rarely found in developed countries or even in some developing nations.

On April 17, 2008, the Zimbabwean government enacted the Indigenisation and Economic Empowerment Act into law to empower indigenous people. Section 3(1) of the Act obliges foreign-owned commercial businesses with an asset value of at least USD 500 000 to cede 51% or more of their shares to indigenous Zimbabweans. Hence, most private firms are owned by the indigenous Zimbabweans, most of whom have deficient or unfitting industry experience and limited managerial skills. The implementation of the Act led to a fall in investor confidence, a reduction in aggregate demand for local goods and services, a decline in firm performance, and deterioration in economic growth, resulting in the failure of several private firms. To avoid massive closures of local firms, the Zimbabwean government launched “Buy Zimbabwe” and “Make Local Buy Local” campaigns promoting home-grown goods and services, and banned certain imports. The resulting increased demand for local goods and services has exposed several private firms to episodes of rapid growth. Given that Zimbabwean private firms are often undercapitalised, rapid growth has been financed through debt. Various local owners have failed to cope with the management challenges that come with rapid growth, leading to high default probabilities. Further, due to incessant viability problems, most private firms that previously exported have either ceased to export, as a way of downsizing, or gone out of business entirely.

Many Zimbabwean private firms have found it difficult to access formal credit from financial institutions because of their high indebtedness and questionable creditworthiness, resulting in firms substituting bank credit with trade credit. Generally, compared to Zimbabwean public firms, Zimbabwean private firms use more leverage, depend more on bank loans and trade credit, are associated with high borrowing costs, invest more, and are smaller in size. Being a smaller size implies limited management skills and less diversification, which indicates more vulnerability to idiosyncratic shocks. In resolving corporate financial distress issues, there is a clear legal structure in Zimbabwe. Distressed companies can apply to the courts either for liquidation or to be placed under judicial management. The Insolvency Act guides liquidation and judicial

management. Hence, the Insolvency Act indirectly influences the default probability for private non-financial firms in a number of diverse dimensions.

The Reserve Bank of Zimbabwe (RBZ) is the principal institution that regulates and supervises the Zimbabwean banking sector, which is dominated by commercial banks in terms of total deposits, total assets and total loans and advances (Reserve Bank of Zimbabwe, 2018). Ownership of commercial banks is spread between the government, foreigners and local individuals and corporates. Defaults are regarded as in-house information of the financial institutions and are indicated only for the customers of the financial institutions. In order to align themselves with international regulatory standards, Zimbabwean banks are implementing Basel II guidelines, spearheaded by the RBZ. However, several banks, mainly local and government-owned banks, do not have sufficient technical capacity to implement Basel II/III, mainly due to the economic challenges that have bedevilled the economy.

This study shows that accounting information is useful in differentiating between defaulted and non-defaulted private firms under distressed financial and economic conditions. The experiment offers evidence indicating that a model that incorporates five accounting ratios combined with one firm characteristic and two macroeconomic variables best explains the likelihood that a Zimbabwean private firm will default. This model has an in-sample classification rate of 98.40%. In particular, the study finds a negative effect on default probability using the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the age of the firm, the real GDP growth rate and the inflation rate, and a positive effect on default probability using the bank debt/total assets, earnings before interest and tax/total liabilities and accounts receivable/net sales ratios. The financial ratios are important because they denote some of the most imperative credit risk factors, namely, profitability, leverage, activity and liquidity (see, for instance, Charalambakis and Garrett, 2019 and Hayden, 2011). The research work also shows that the forecasting results of default prediction models are improved by incorporating macroeconomic variables. This finding is consistent with the discovery of Sheikh and Yahya (2015) and Hill, Perry and Andes (2011), who posited that the forecasting results of bankruptcy prediction models are improved by including macroeconomic variables.

The rest of the chapter is organised as follows. In section 3.2, a brief overview of the methodology is outlined. Section 3.3 is allocated to sample and data discussion, and

section 3.4 states experimental results. Finally, section 3.5 presents conclusions and potential directions for future research.

3.2 Methodology

Over the years, the forecasting capacity of standard accounting-based bankruptcy models has been declining (Beaver, Correia and McNichols, 2012; Beaver, McNichols and Rhie, 2005). Henceforth, several studies (see, for instance, Beaver, Correia and McNichols, 2012; Agarwal and Taffler, 2008) propounded that supplementary explanatory variables need to be included in the bankruptcy forecasting models. Altman (2018), Gupta, Gregoriou and Healy (2015) and Altman, Sabato and Wilson (2010) indicated that non-financial variables augment the predictive power of bankruptcy prediction models. Moreover, a private firm default model premised on only firm-specific factors is not proficient in describing the cyclical nature of the witnessed defaults (Jensen, Lando and Medhat, 2017). Jensen, Lando and Medhat (2017) posited that macroeconomic factors and accounting ratios are crucial in default forecasting for privately-owned corporations. The authors proposed that the effects of firm-specific factors remain robust to the addition of the macroeconomic variables. The reviewed literature indicated that the predictive capacity of private firm bankruptcy models is enhanced by combining financial ratios with firm and loan characteristics and macroeconomic variables (Charalambakis and Garrett, 2019; Charalambakis, 2014). This study generates stepwise logit models based on diverse combinations of loan and firm characteristics, financial ratios and macroeconomic factors, and implements the stepwise selection of some threshold criteria to predict default for Zimbabwean privately-owned corporations under downturn conditions twelve months in advance.

In corporate default prediction, the logistic regression is a kind of multivariate statistical models that has been widely used (Becerra-Vicario et al., 2020; Durica, Valaskova and Janoskova, 2019; Altman et al., 2017; Kovacova and Kliestik, 2017; Mendelova and Stachova, 2016; Hayden, 2011). This study adopts a logit model because it provides several benefits. Logistic regression has been extensively applied in corporate default prediction mainly due to its easy-to-use nature, reliability and high classification rate (see, for instance, Becerra-Vicario et al., 2020; Durica, Valaskova and Janoskova, 2019; Altman et al., 2017; Kovacova and Kliestikova, 2017; Bateni and Asghari, 2016). In designing and estimating rating techniques, Hayden (2011) proposed that the logit

model is the most popular statistical model in practice and also in the academic literature since its output can be easily inferred as probability of default and it permits a simple check of the economic meaningfulness of the practical dependence between the prospective predictor variables and the default risk. Durica, Valaskova and Janoskova (2019) and Kliestik, Kocisova and Misankova (2015) and references therein indicated that logistic regression is flexible when using real-world data, since it does not assume normal distribution, linearity and independence among independent covariates. Also, Durica, Valaskova and Janoskova (2019), Obradovic et al. (2018), Kliestik, Kocisova and Misankova (2015) and Kliestik et al. (2014) posited that logistic regression has less restrictive statistical requirements than other statistical models such as multiple discriminant and probit models. Hence, a logit model accurately describes in a simple manner the behaviour of probability of default.

A brief overview of the binary logistic regression model used in predicting the default probability is illustrated here. A two-class classification problem based on defaulted and non-defaulted private firm loan accounts is considered, that is, the default probability takes only two values, 1 if default happens and 0 if default does not happen. The logit score is given by

$$P_i(z) = \frac{1}{1+\exp(-z_i)},$$

where, for the *i*th account, z_i is the dependent variable and $P_i(z)$ is the default probability given a particular set of predictors. Here, z_i is described by

$$z_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \mu_i,$$

where, β_1, β_2, ..., β_k are regression coefficients, β_0 denotes the intercept, x_1, ..., x_k represent a set of *k* predictor variables (i.e., firm and loan characteristics, financial ratios and macroeconomic factors) and μ_i refers to the error term. The study includes macroeconomic factors and financial ratios with a time lag of twelve months.

In this study, omnibus tests, Hosmer-Lemeshow tests and pseudo R^2 measures (Cox and Snell R^2 and Nagelkerke R^2) are implemented to analyse the goodness-of-fit of the designed models.

3.3 Sample and data

In this experiment, the study uses a unique cross-sectional real-world data set of private firm defaulted and non-defaulted loan accounts (with a binary response variable) selected from a credit portfolio of an anonymous major Zimbabwean commercial bank over the observation period from 2010 to 2018 to create stepwise logit models. The initial sample has a total of 194 defaulted and non-defaulted private firms. The study excludes state-owned, financial and multinational institutions that do not show the true characteristics of typical Zimbabwean private firms. Loan accounts are observed and tracked annually. The study eliminates from the sample financial statements that cover time horizons of less than twelve months and loan accounts that are recorded more than once, i.e., duplicates. After data cleaning, 191 companies (that is, 39 defaulted and 152 non-defaulted) are left in the final sample.

In order to discover which drivers are associated with the default probability for private firms, the research focuses on a set of drivers of twenty financial ratios (see Table 3.1), six firm and loan characteristics and six macroeconomic variables (see Table 3.2). The study adopts, in the first step, predictor variables that are popular in academic literature, appropriate to the experiment and have superior predictive power in empirical researches, intending to improve the forecasting capabilities of the designed models. The study implements, in the second step, a stepwise selection technique with forward elimination to choose the most statistically significant drivers of default probability. In deriving financial ratios, for defaulted firms the study examines the last set of financial statements filed a year before default since a modelling or forecast horizon is set at one year, and for non-defaulted firms the study analyses their latest financial statements filed since they give the most current financial position of the firms. This forecasting horizon is long enough to permit banks to take some corrective action to avoid forecasted defaults and short enough to warranty the aptness of the data input into the rating model (see, for instance, Hayden 2011 and Basel Committee on Banking Supervision, 1999). The study gathers firm and loan characteristics at the time of loan application. Macroeconomic factors, lagged twelve months before default, are sourced from the World Bank Group. Tables 3.1 and 3.2 also depict the expected relationships linking probability of default and the covariates. A positive sign indicates that if the value of the predictor increases, the likelihood of default rises. Conversely, a negative sign indicates that if the predictor's value rises, the probability of default falls.

Table 3. 1 Financial ratios

Abbreviation	Financial ratio	Risk factor	Expected effect	Source
TL/TA	Total liabilities/total assets	Leverage	+	Becerra-Vicario et al. (2020)
EQ/TA	Equity/total assets	Leverage	-	Hayden (2011)
BD/TA	Bank debt/total assets	Leverage	+	Hayden (2011)
SD/TA	Short-term debt/total assets	Leverage	+	Hayden (2011)
CA/CL	Currents assets/current liabilities	Liquidity	-	Ogachi et al. (2020)
AR/NS	Accounts receivable/net sales	Activity	+	Hayden (2011)
AP/NS	Accounts payable/net sales	Activity	+	Hayden (2011)
(NS-MC)/PC	(Net sales – material costs)/ personnel costs	Productivity	-	Hayden (2011)
NS/TA	Net sales/total assets	Turnover	-	Hayden (2011)
EBIT/TA	Earnings before interest and tax/ total assets	Profitability	-	Stefko, Horvathova and Mokrisova (2020)
OBI/TA	Ordinary business income/ total assets	Profitability	-	Hayden (2011)
TA	Total assets	Size	-	Charalambakis and Garrett (2019)
(CA-CL)/TA	(Current assets – current liabilities)/ total assets	Liquidity	-	Durica, Valaskova and Janoskova (2019)
EBIT/EQ	Earnings before interest and tax/ equity	Profitability	-	Charitou, Neophytou and Charalambous (2004)
NS/NSLY	Net sales/net sales last year	Growth	-/+	Hayden (2011)
TL/TLLY	Total liabilities/ total liabilities last year	Leverage growth	+	Hayden (2011)
EBIT/TL	Earnings before interest and tax/ total liabilities	Leverage	-	Wang (2011)
CL/TA	Current liabilities/total assets	Leverage	+	Al-Kassar and Soileau (2014)

TL/EQ	Total liabilities/equity	Leverage	+	Gallo (2015); Keener (2013)
CA/TA	Current assets/total assets	Liquidity	-	Durica and Svabova (2019).

The study chooses financial ratios that represent significant credit risk factors in default prediction, i.e., leverage, leverage growth, profitability, productivity, liquidity, turnover, firm size, growth and activity. Some financial ratios, such as the (net sales – material costs)/personnel costs, equity/total assets and total liabilities/equity ratios, indicate the diverse financial features of the borrowing firm that are important in default risk modelling covering deep and complex economic problems. Hayden (2011) proposed that the use of dynamic ratios that compare current to past levels of particular balance-sheet items is imperative in forecasting default events. Thus, the research also incorporates dynamic financial ratios, for example, the ratio of net sales/net sales last year.

Table 3. 2 Firm and loan characteristics and macroeconomic factors

Abbreviation	Variable	Expected effect	Source
Panel A: Firm and loan characteristics			
LN	Loan amount	+	Bohorquez, Matienzo and Olivares (2013)
INT	Interest rate	+	Michalkova, Adamko and Kovacova (2018)
AG	Age of the firm	-	Succurro (2017)
CTV	Collateral value	-	Bauer and Edresz (2016); Bohorquez, Matienzo and Olivares (2013)
TwB	Time with the bank	-	Jensen, Lando and Medhat (2017)
LMP	Loan maturity period	+	Bohorquez, Matienzo and Olivares (2013)
Panel B: Macroeconomic factors			
GNIC	Gross national income per capita growth	-	-
RGDP	Real GDP growth rate	-	Charalambakis and Garrett (2019); Jensen, Lando and Medhat (2017)
INF	Inflation rate (% yearly average)	+	Rezende et al. (2017)
BB	Budget balance (% GDP)	+	-

PDE	Public debt (% GDP)	+	-
UR	Unemployment rate	+	Korol (2017)

Table 3.2 shows the firm and loan characteristics and macroeconomic variables included in this study together with their expected effect on default probability. Corporate exposures referred to here are commercial loans (excluding mortgage loans or lines of credit). The loan amount refers to the initial sum of money advanced to the firm, while the interest rate is the original contractual interest rate charged to the corporate borrower. The firm's age represents the time (in years) from the day of its incorporation to the date of the loan application. Collateral value denotes the value of collateral pledged by the borrower when getting a loan. Types of collateral include equipment, land, residential real estate and commercial real estate but exclude personal guarantees. Time with the bank is the time (in years) the borrower has been in a business relationship with a particular bank, that is, the period over which a corporate borrower has been using a particular bank as its lender. Lastly, the loan maturity period refers to the term (in years) of the loan advanced.

Instead of eliminating observations with missing values, the study imputes the missing values to reduce bias and increase precision. The study adopts mean imputation because it is not computationally demanding, it is fast and it maintains the sample size (Song and Shepperd, 2007). In this method, the mean of the non-missing values for each predictor variable with missing value(s) is computed. The study then replaces each missing value with the calculated mean. The short-term debt/total assets and accounts payable/net sales ratios are each missing 1.05% of their values, while the ratio of ordinary business income/total assets and the interest rate are each missing 0.52% of their values. This translates into 2.09% of firms with missing values. The study observes that 2.56% and 1.97% of defaulted and non-defaulted firms, respectively, have missing values. This shows that missing values are more common for defaulted firms than for non-defaulted firms. Outliers can significantly misrepresent the computed model parameters and lead to incorrect inferences. To avoid the elimination of the outliers from the sample, the study winsorizes extreme data points at the distribution's 1^{st} and 99^{th} percentiles.

Table 3.3 presents the descriptive statistics for financial ratios, firm and loan characteristics and macroeconomic factors for the whole sample. It reports the

minimum, maximum, mean and standard deviation values for the financial ratios, firm and loan characteristics and macroeconomic factors based on the entire private firm sample.

Table 3. 3 Financial ratios, firm and loan characteristics and macroeconomic factors with descriptive statistics

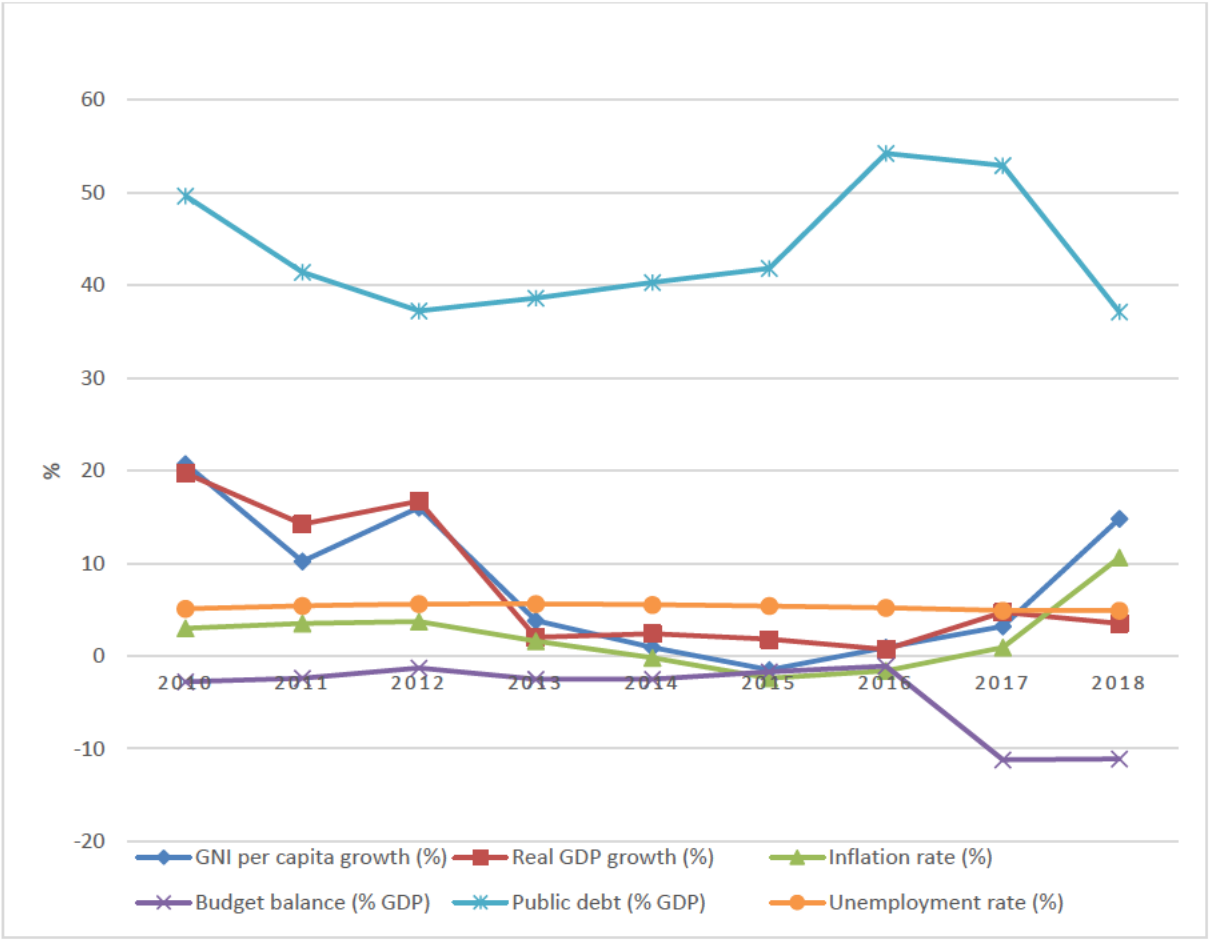
Variable	Min	Max	Mean	SD
Panel A: Financial ratios				
TL/TA	0.03	1.42	0.76	0.33
EQ/TA	-0.42	0.97	0.29	0.27
BD/TA	0.00	0.71	0.15	0.16
SD/TA	0.00	0.82	0.18	0.19
CA/CL	0.37	3.90	1.30	0.74
AR/NS	0.01	1.94	0.30	0.35
AP/NS	0.00	1.46	0.24	0.26
(NS-MC)/PC	-1.57	5.92	2.71	1.45
NS/TA	0.11	4.56	1.66	1.27
EBIT/TA	-0.48	0.40	0.04	0.14
OBI/TA	0.11	5.15	1.88	1.55
TA*	3.13	212.37	34.99	56.54
(CA-CL)/TA	-0.56	0.97	0.08	0.31
EBIT/EQ	-3.47	5.67	0.32	1.24
NS/NSLY	0.24	3.42	1.13	0.59
TL/TLLY	0.08	4.95	1.40	1.03
EBIT/TL	-1.08	2.57	0.14	0.45
CL/TA	0.02	1.19	0.55	0.29
TL/EQ	-3.40	5.15	2.10	2.40
CA/TA	0.10	1.00	0.63	0.27
Panel B: Firm and loan characteristics				
LN*	0.07	10.00	2.09	2.19
INT	3.00	24.00	13.62	4.61
AG	2.00	79.00	25.48	23.17

CTV*	0.00	7.00	1.18	1.62
TwB	1.00	19.00	6.51	4.61
LMP	1.00	9.00	1.23	1.16
Panel C: Macroeconomic factors				
GNIC	-1.5	20.7	5.16	6.89
RGDP	0.7	19.7	5.25	6.28
INF	-2.4	10.6	0.96	3.17
BB	-11.2	-1.1	-2.99	3.01
PDE	37.10	54.2	43.67	6.47
UR	4.9	5.6	5.36	0.23

SD denotes standard deviation. *In millions of US dollars.

Figure 3.1 shows the trends of the selected macroeconomic variables throughout the observation period. The graph indicates that the economy has been embroiled in a severe economic crisis characterised by negative and low rates of inflation, which has adversely affected the country's growth. Lack of fiscal cautiousness has led to extended fiscal deficits, resulting in deep and complex macroeconomic and fiscal difficulties.

Figure 3.1 Trends of macroeconomic variables from 2010 to 2018



3.4 Empirical results

3.4.1 Model estimation

The study uses the entire final sample of 191 firms to fit the models of interest. Due to its small size, the study opts against splitting the sample into a test sample and a validation sample because it may introduce limitations (Yun and Goodacre, 2018). The study uses a stepwise selection technique with forward elimination to select the most statistically significant predictors at a 95% level of confidence. The probabilities required for variables to enter and be removed from the regression equation are set at 0.05 and 0.10, respectively, while developing models I and II. However, it has emerged that the choice of 0.05 as the entry probability and 0.1 as the elimination probability is too strict, in most cases eliminating significant predictors from the modelling framework (Sarkar, Midi and Rana, 2010). To include all statistically significant variables associated with the response variable in stepwise regression analysis, Hosmer and Lemeshow (2000) proposed the adoption of 0.15 and 0.20 as the entry and removal probabilities, respectively. Hence, the study applies 0.15 as the entry probability and

0.20 as the removal probability in building models III and IV. Given two highly correlated predictor variables, the study removes one of them from the model(s) to solve the problem of multicollinearity. Hence, all designed models are not affected by multicollinearity (see Table 3.4).

Table 3. 4 Correlation coefficient matrix for the variables included in the models

	BD/TA	SD/TA	AR/NS	EBIT/TA	(CA-CL)/TA	EBIT/TL	CA/TA	NS/NSLY	AG	TwB	RGDP	INF
BD/TA	1											
SD/TA	0.512	1										
AR/NS	0.005	-0.128	1									
EBIT/TA	-0.217	-0.166	-0.286	1								
(CA-CL)/TA	-0.189	-0.242	0.250	0.195	1							
EBIT/TL	-0.181	-0.164	-0.286	0.607	0.163	1						
CA/TA	0.000	-0.041	0.034	0.044	0.539	-0.176	1					
NS/NSLY	-0.200	-0.173	-0.229	0.146	-0.098	0.008	0.022	1				
AG	0.006	0.104	0.192	-0.114	0.043	-0.163	-0.248	-0.083	1			
TwB	-0.045	0.127	-0.190	0.101	-0.013	-0.011	0.032	-0.074	0.458	1		
RGDP	-0.148	0.012	0.000	0.054	0.059	-0.079	-0.059	-0.043	0.103	0.174	1	
INF	-0.119	0.004	0.094	-0.019	-0.006	-0.131	-0.137	-0.003	0.018	0.078	0.478	1

The study proposes four stepwise logistic regression models using different combinations of firm and loan characteristics, financial ratios and macroeconomic factors and some threshold in forward stepwise selection. Models 1 and II include financial ratios and firm and loan characteristics but differ in entry and removal probabilities. In model I, the study uses 0.05 and 0.10 as the entry and removal probabilities, respectively. In model II, the study adopts 0.15 and 0.20 as the entry and 0.20 removal probabilities, respectively. Models III and IV include financial ratios, firm and loan characteristics and macroeconomic factors. In model III, the research uses 0.05 and 0.10 and in model IV the study uses 0.15 and 0.20 as the entry and removal probabilities in stepwise selection, respectively.

3.4.2 Predictive ability of the logit models

The assessment of the predictive performance of default probability models plays a crucial role in the development of modelling frameworks. For this binary classification problem, the study describes the classifiers' performance using the 2 x 2 confusion matrix indicated in Table 3.4. Abedin et al. (2018) and Guotai, Abedin and Moula (2017) indicated that the confusion matrix reveals the following four outcomes.

(i) True positive (TP): category of bad borrower correctly identified as bad.

(ii) False positive (FP): class of good obligor wrongly pinpointed as bad.

(iii) False negative (FN): category of bad applicant wrongly identified as good.

(iv) True negative (TN): category of good borrower rightly pinpointed as good.

Table 3. 5 The 2 x 2 confusion matrix for a classification problem

	Predicted observations		
	Predicted negative	**Predicted positive**	
Actual observations			
Actual negative	TN	FP	**ON**
Actual positive	FN	TP	**OP**
	PN	**PP**	**TOTAL**

PN (predicted negative) is equal to FN + TN. PP (predicted positive) is equal to FP + TP. ON (observed negative) is equal to TN + FP. OP (observed positive) is equal to FN + TP. TOTAL (total number of observations) = TP + FP + FN + TN.

The study uses the in-sample classification rate and type I and type II error rates to evaluate the performance of the models. The classification rate indicates the percentage of firms predicted properly. The type I error rate is the rate at which good borrowers are classified as bad, while type II error rate refers to the rate at which bad obligors are categorised as good. The classification rate and type I and type II error rates for the stepwise logit models are examined for cut-off points from 0.1 to 0.9 at the 5% significance level. These assessment metrics are computed as follows:

$$\text{classification rate} = \frac{TP+TN}{TOTAL},$$

$$\text{type I error rate} = \frac{FP}{FP+TN},$$

$$\text{type II error rate} = \frac{FN}{FN+TP}.$$

Table 3.6 outlines the in-sample classification rate and type I and type II error rates for all four models.

Table 3. 6 Cut-off points, classification rates and type I error and type II error rates for model I - IV

Cut-off point	Classification rate (%)	Type I error rate (%)	Type II error rate (%)
Panel A: Model I			
0.1	79.60	23.68	7.69
0.2	83.80	14.47	23.08
0.3	89.50	7.24	23.08
0.4	90.10	4.61	30.78
0.5	92.10	1.97	30.77
0.6	93.70	0.00	30.78
0.7	92.10	0.00	38.46
0.8	89.50	0.00	51.28
0.9	88.00	0.00	58.97
Panel B: Model II			
0.1	82.70	21.71	0.00
0.2	82.70	21.71	0.00
0.3	92.10	7.89	7.69
0.4	90.60	7.89	15.38
0.5	85.90	7.89	38.46
0.6	85.90	7.89	38.46
0.7	88.00	0.00	58.97
0.8	88.00	0.00	58.97
0.9	85.30	0.00	71.79
Panel C: Model III			
0.1	91.60	10.53	0.00
0.2	92.70	8.55	2.56
0.3	94.80	5.26	5.13
0.4	94.80	4.61	7.69
0.5	93.20	4.61	15.38
0.6	95.30	1.97	15.38
0.7	92.10	1.32	33.33
0.8	92.70	0.66	33.33
0.9	91.10	0.66	41.03
Panel D: Model IV			
0.1	96.90	3.95	0.00
0.2	96.90	3.95	0.00

0.3	98.40	1.97	0.00
0.4	98.40	1.97	0.00
0.5	96.90	1.97	7.69
0.6	96.90	1.97	7.69
0.7	95.30	1.97	15.38
0.8	93.20	1.97	25.64
0.9	93.20	0.00	33.33

Numerous studies have suggested several criteria for setting optimal cut-off points (see, for example, Sabela et al., 2018). In this study, cut-off points at which the sum of type 1 and type II error rates is minimal and the overall model performance is high are selected. In model I, the cut-off point of 0.3 has a minimal sum of the two errors of 30.32% (7.24% + 23.08%) and a model in-sample classification rate of 89.50%. Therefore, a cut-off of 0.3 optimises model I. In the same vein, a cut-off point of 0.3 optimises models II and III. Model IV is optimised by cut-off points 0.3 and 0.4.

3.4.3 Discussion

The results for each model developed are presented and discussed in this section. The study examines the drivers of the default probability for Zimbabwean private firms using four stepwise logit models. To analyse the significance of the predictors incorporated into the logistic regression models, the study uses the Wald test. If the Wald test p-value of the variable is below the 5% confidence level (typically $p \leq 0.05$), it indicates that the variable notably contributes to the model's forecasting capacity. Conversely, if the Wald test p-value of the predictor is above the 5% confidence level ($p > 0.05$), it shows that the predictor is statistically insignificant. The study removes predictor variables with $p > 0.05$ from the models and includes predictor variables with $p \leq 0.05$.

The mean imputation of missing values may potentially bias the results. However, the study confirms that the modelling results generated after the mean imputation of missing values and winsorization of outliers are more robust than those produced when observations with missing values and outliers are omitted from the modelling framework. For brevity, results generated after excluding observations with missing values and outliers from the modelling framework are not reported in this study.

3.4.3.1 Model I

Table 3.7 provides the details of variables incorporated into model 1.

Table 3. 7 Model I results reflecting coefficient estimates

Variable	Coefficient	Wald	Significance
BD/TA	2.869	17.325	0.000
STD/TA	1.667	11.576	0.001
EBIT/TA	-3.760	8.082	0.004
(CA-CL)/TA	-0.725	11.100	0.001
EBIT/TL	1.018	10.905	0.001
NS/NSLY	0.833	9.450	0.002
TwB	-0.477	26.519	0.000
Constant	0.866	4.413	0.036

See Table 3.1 for ratio definitions.

The results show that all variables included in model I are significantly related to the default probability for Zimbabwean private firms, with the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets and the time with the bank having a negative effect on the default probability, while the bank debt/total assets ratio, the ratio of short-term debt/total assets, the earnings before interest and tax/total liabilities ratio and the ratio of net sales/net sales last year having a positive effect on the default probability.

As a profitability measure, the earnings before interest and tax/total assets ratio has a negative sign, which is in line with that presented in the literature for public and private firms in both advanced and developing economies. This finding is not surprising given that high profitability increases the value of a corporate's equity and indicates that a corporate needs more time for its costs to increase or revenues to fall before a default occurs. The negative correlation between profitability and the default probability has been associated with, among other countries, Austria (Hayden, 2011), the US (Ohlson, 1980; Shumway, 2001), Greece (Charalambakis, 2015) and India (Charalambakis and Garrett, 2016). Charalambakis and Garrett (2019) and Charalambakis (2014) revealed

that there is a negative relationship between profitability and the probability of financial distress for Greek privately-traded companies. Moreover, Altman, Sabato and Wilson (2010) and Altman and Sabato (2007) discovered a negative association between the probability of financial distress and profitability for small-to-medium enterprises (SMEs) in the United Kingdom (UK) and US, respectively.

It is observed that liquidity is a key measure of default risk. The ratio of (current assets-current liabilities)/total assets enters model I with a negative sign, as expected. Thus, liquidity considerably and negatively affects the default probability for Zimbabwean private firms, signifying that the more liquid they are, the less likely they are to default on their loans. Given that Zimbabwean private firms are operating in an illiquid market, high liquidity enables them to meet their short-term commitments. This discovery is in agreement with the findings of Altman, Sabato and Wilson (2010) for UK SMEs and Altman and Sabato (2007) for US SMEs. In addition, Charalambakis and Garrett (2019) and Charalambakis (2014) revealed a negative correlation between liquidity and the probability of financial distress for Greek private firms.

Time with the bank has a negative sign, expected. This means that loans of private firms with long-term lending relationships with their banks before loan acquisition are associated with low probability of default. Long-term firm-bank relationships are valuable to high-risk Zimbabwean private firms. Zimbabwean private firms with long-term relationships with banks are better able to withstand downturn conditions than firms with short-term relationships with banks. They are able to withstand downturn conditions because they benefit from reduced bank loan interest rates, low prices for services provided by the banks and from guarantees to get credit from banks even under distressed economic and financial conditions (banks usually lend to firms they knew before the emergence of strained economic and financial conditions). Assurance to get credit increases the availability of financial resources under illiquid conditions. Further, Zimbabwean private firms with long-term relationships with banks can renegotiate their credit conditions and can reduce the risk of information asymmetry, i.e., long-term relationships provide the bank with more information about the borrower than is often contained in financial statements. Congruent to this finding, Peltoniemi (2007) propounded that long-term firm-bank relationships are particularly valuable to high-risk corporates, and Petersen (1999) argued that a lending relationship between a corporate borrower and bank creates value to the borrowing firm in the form of assurance to get credit and low interest rates, among other benefits. Bodenhorn (2003) found that firms

with long-term firm-bank relationships benefit from lower costs of credit, fewer personal guarantees required when borrowing, and renegotiable loan terms during a credit crunch. Significantly, these authors indicated that firms with long-term firm-bank relationships are associated with low probability of default.

The study anticipates that leverage measures, the bank debt/total assets and short-term debt/total assets ratios have positive signs, which are consistent with those presented in the existent literature (see Brindescu-Olariu, 2016; Charalambakis, 2015, 2014; Hayden, 2011). Charalambakis and Garrett (2019) found a positive relationship between leverage and the probability of financial distress for Greek privately-traded companies. Moreover, Altman, Sabato and Wilson (2010) and Altman and Sabato (2007) revealed a positive relationship between leverage and the probability of financial distress for UK and US SMEs, respectively. Zimbabwean private firms are often undercapitalised. Hence, they use debt to finance growth and their working capital needs. However, the use of high leverage reduces their cover against adverse shocks, especially exogenous liquidity shocks. In the same vein, Falkenstein, Boral and Carty (2000) showed that as the gearing or leverage used by firms increases, the cushion against adverse shocks becomes smaller. Zimbabwean private firms that take on more debt under downturn conditions lead to higher rates of default because income must be used to pay back the debts even if earnings or cash flows go down. Moreover, credit comes at a cost that adversely affects customers' ability to repay debts (Aleksanyan and Huiban, 2016). Due to significant managerial errors resulting from inadequate or unsuitable industry experience and limited skills, Zimbabwean private firms fail to meet their obligations under distressed conditions.

The study does not have a prior expectation of either a positive or negative sign for the regression coefficient for the net sales/net sales last year ratio. In this study, it is noted that the correlation between default probability and the ratio of net sales/net sales last year is positive, indicating that, as the ratio increases, the default probability increases. It is desirable, in practice, for a corporate to grow instead of scaling down. However, high sales growth is a major source of high default risk, as indicated here. Zimbabwean private firms have experienced phases of growth due to an increase in demand for local goods and services due to the introduction of “Buy Zimbabwe” and “Make Local Buy Local” campaigns by the government. Given that most Zimbabwean private firms are owned by the indigenous people with limited management abilities, the owners find it

difficult to cope with the management challenges that arise as a result of the rapid growth. Moreover, the rapid growth of sales has been financed through debt which is challenging to service for several Zimbabwean private firms due to continuous viability problems and their vulnerability to idiosyncratic shocks. Another possible explanation for the positive correlation between default probability and the ratio of net sales/net sales last year is that the sales growth has been driven by credit sales which turned into irrecoverable debts. Using the same line of reasoning, Hayden (2011) found a positive relationship between default probability for Austrian firms and the ratio of the net sales/net sales last year and argued that, in most cases, firms that expand very rapidly might fail to deal with the management difficulties that emerge as a result of swift growth. Falkenstein, Boral and Carty (2000) posited that high sales growth means that a firm is growing swiftly and that rapid growth is not likely to be financed by generated profits, leading to an increase in debt and other related risks such as bankruptcy.

In this study, the prior expectation is that the coefficient for the ratio of the earnings before interest and tax/total liabilities is negative. However, the study finds that the earnings before interest and tax/total liabilities ratio is associated with a positive regression coefficient, suggesting that the default probability rises as the ratio increases. This finding goes against intuition, but the results are more driven by the denominator (total liabilities) than the numerator (earnings before interest and tax). Large levels of the ratio of earnings before interest and tax/total liabilities for Zimbabwean private firms result from low levels of total liabilities due to reduced levels of trade credit. Several Zimbabwean private firms are of questionable creditworthiness and are embroiled in debt. Consequently, they cannot easily access formal credit from financial institutions. They depend more on trade credit from suppliers as a substitute for formal credit from financial institutions. However, financially distressed firms find it difficult to obtain trade credit from suppliers to maintain their sales. Even if they manage to access trade credit, its supply only lasts for a short time before the suppliers themselves become credit restricted and then decrease trade credit levels. Bastos and Pindado (2013) confirmed the substitution hypothesis between trade credit and bank credit in the context of a financial crisis. They concluded that suppliers offset credit shrinking from financial organizations when giving trade credit to less creditworthy companies. They further suggested that, during financial crises, suppliers grant trade credit for a short period before they become credit constrained and reduce trade credit level. Generally, due to the prevailing liquidity crisis, suppliers have restricted access to formal credit,

resulting in them having smaller cash holdings. This translates into reduced levels of trade credit to customer firms. In support of this, Shenoy and Williams (2017) indicated that suppliers with more access to bank liquidity provide more trade credit to their customers, and suppliers with less access to bank liquidity provide less trade credit to their customers. Such restrictions on trade credit push distressed firms into default, given that no other credit source is accessible to them.

3.4.3.2 Model II

Model II results are presented in Table 3.8.

Table 3. 8 Model II results reflecting coefficient estimates

Variable	Coefficient	Wald	Significance
BD/TA	3.869	15.096	0.000
STD/TA	0.865	6.736	0.009
EBIT/TA	-2.960	6.515	0.011
(CA-CL)/TA	-1.011	15.097	0.000
EBIT/TL	2.977	18.406	0.000
CA/TA	0.275	10.454	0.001
NS/NSLY	0.964	6.133	0.013
TwB	-0.297	14.440	0.000
Constant	2.855	18.452	0.000

See Table 3.1 for ratio definitions.

The experimental results show that all the variables included in model II are highly correlated with the default probability for Zimbabwean private firms, with the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets and the time with the bank having a negative effect on the default probability, and the bank debt/total assets ratio, the ratio of short-term debt/total assets, the net sales/net sales last year ratio, the ratio of earnings before interest and tax/total liabilities and the ratio of current assets/total assets having a positive effect on the default probability. It is observed that the signs for the estimated coefficients for the bank debt/total assets, short-term debt/total assets, earnings before interest and tax/total assets, earnings before interest and tax/total liabilities, (current assets – current

liabilities)/total assets and net sales/net sales last year ratios and the time with the bank are similar to those in model I.

This experiment does not have a prior expectation of the positive sign for the coefficient for the ratio of current assets/total assets. The positive sign associated with the current assets/total assets ratio differs from the sign proposed in the literature (see, for example, Hayden 2011); it goes against intuition. Nevertheless, this result is more driven by the numerator (current assets) than the denominator (total assets). Due to the prolonged liquidity squeeze in the Zimbabwean currency system, several customers use trade credit, as they cannot buy goods on cash on delivery with restricted terms. As a result, several private firms have higher levels of accounts receivable, which they cannot amass quickly. This implies that private firms with high levels of accounts receivable also end up delaying or failing to make payments to their creditors, leading to a credit contagion cascading effect. Using the same line of reasoning, Bastos and Pindado (2013) suggested that trade credit contagion in the supply chain frequently happens during a financial crisis. Jorian and Zhang (2009) confirmed that trade credit interactions could spread credit contagion in industrial companies.

3.4.3.3 Model III

The regression coefficients for the predictor variables incorporated into model III are indicated in Table 3.9.

Table 3. 9 Model III results reflecting coefficient estimates

Variable	Coefficient	Wald	Significance
BD/TA	1.035	4.159	0.041
AR/NS	2.150	14.612	0.000
EBIT/TA	-2.623	15.812	0.000
(CA-CL)/TA	-0.490	16.891	0.000
EBIT/TL	0.895	6.885	0.009
AG	-1.648	11.742	0.001
RGDP	-1.525	9.588	0.002
Constant	2.355	17.472	0.000

See Table 3.1 for ratio definitions.

The results show that all variables included in model III are significantly related to the default probability for Zimbabwean private firms, with the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the age of the firm and the real GDP growth rate having a negative effect on probability of default, and the bank debt/total assets, accounts receivable/net sales and earnings before interest and tax/total liabilities ratios having a positive effect on probability of default. It is observed that the signs for the estimated coefficients for the bank debt/total assets, earnings before interest and tax/total assets, earnings before interest and tax/total liabilities and (current assets-current liabilities)/total assets ratios behave as in models I and II.

This study reveals that the real GDP growth rate is a significant determinant of the default probability for Zimbabwean private firms. The growth rate of real GDP enters model III with a negative sign, which is expected, indicating that the default probability decreases as the real GDP growth rate rises. This finding is not surprising, considering that an increase in the real GDP growth rate shows that the economy is performing well. In agreement with this finding, Charalambakis and Garrett (2019) highlighted that the real GDP growth rate is negatively correlated with the probability of financial distress for Greek private firms.

Firm age dynamics have a significant influence on the mortality rates of Zimbabwean private firms. The coefficient for the age of the firm is statistically significant and has a negative sign, showing that young firms are associated with a higher risk of default than mature corporates. Youthful Zimbabwean private firms are faced with severe interior challenges and wrestle more with economic downturns and greater competition. In line with this finding, Succurro (2017) and Kenney, Cava and Rodgers (2016) suggested that young and adolescent firms are characterised by higher default risk than mature and established corporates due to several challenges, including stiff competition. However, this finding is not inconsistent with that of Switzer, Wang and Zhang (2018), who suggested that firm age and default risk are positively correlated.

The study finds that the accounts receivable/net sales ratio significantly and positively influences the default probability for Zimbabwean private firms, as expected, suggesting that probability of default rises as the ratio increases. This is in line with the findings of Hayden (2011), who proffered that the accounts receivable/net sales ratio substantially and positively influences the default probability for Austrian firms. Due to the liquidity crisis in Zimbabwe, several private firms have higher levels of accounts receivable due to the inability of customers to buy goods on restricted terms such as cash on delivery. High levels of accounts receivable create default risk for the firms because they cannot be collected in time, thereby negatively affecting firm's liquidity, profitability and cash flow positions. Moreover, an increase in accounts receivable leads to higher contagion risk from the default of debtors, resulting in credit losses to the creditors. These credit losses then drive the trade creditors into default and, subsequently, bankruptcy.

3.4.3.4 Model IV

The results for model IV are reported in Table 3.10.

Table 3. 10 Model IV results reflecting coefficient estimates

Variable	Coefficient	Wald	Significance
BD/TA	1.487	9.373	0.002
AR/NS	1.257	8.342	0.004
EBIT/TA	-0.617	7.290	0.007
(CA-CL)/TA	-3.129	4.723	0.030
EBIT/TL	0.700	4.648	0.031
AG	-0.563	27.521	0.000
RGDP	-1.572	9.859	0.002
INF	-0.239	9.842	0.002
Constant	0.818	5.406	0.020

See Table 3.1for ratio definitions.

The experimental results show that all the predictor variables included in model IV are significantly associated with the default probability for Zimbabwean private firms, with the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the age of the firm, the real GDP growth rate and the inflation rate having a negative effect on the default probability, and the bank debt/total assets, accounts receivable/net sales and earnings before interest and tax/total liabilities ratios having a positive effect on the default probability. The study notes that the signs for the estimated coefficients for the bank debt/total assets, earnings before interest and tax/total assets, earnings before interest and tax/total liabilities, and (current assets-current liabilities)/total assets ratios behave as in models I and II. The real GDP growth rate and the firm's age enter model IV with a negative sign, while the accounts receivable/net sales ratio enters model IV with a positive sign, as in model III.

This study does not have a prior expectation of the negative sign for the coefficient for the inflation rate, which plainly goes against intuition. The coefficient for the inflation rate is significant and has a negative sign, revealing that, as the inflation rate increases, the default probability drops. Inflation benefits borrowers by reducing the real value of loans, thereby making it easier for them to pay their loans. Moreover, the observation period under consideration is characterised by deflation. Deflation leads to reduced

overall economic activity, a fall in investment, a rise in the real value of debt and an increase in the unemployment rate (see, for example, Mahonde, 2016). Masiyandima et al. (2018) argued that the emergence of the US dollar as the major currency in Zimbabwe led to negative and low rates of inflation, which impacted negatively on the country's growth. Deflation also aggravated the recession in Zimbabwe and led to a deflationary spiral. The rise in the real value of debts due to deflation makes it difficult for Zimbabwean private firms to repay outstanding loans, leading to high default rates.

3.4.4 Goodness-of-fit measures

In this study, omnibus tests (Table 3.11), Hosmer-Lemeshow tests (Table 3.12), and pseudo R^2 measures (Cox and Snell R^2 and Nagelkerke R^2) (Table 3.13) are implemented to analyse the goodness-of-fit of the designed models.

Table 3. 11 Omnibus tests of model coefficients

		Chi-square	**df**	**Significance**
Model I	Step	6.228	1	0.013
	Block	95.505	7	0.000
	Model	95.507	7	0.000
Model II	Step	32.714	1	0.000
	Block	117.566	7	0.000
	Model	117.566	7	0.000
Model III	Step	6.113	1	0.013
	Block	147.594	14	0.000
	Model	147.594	14	0.000
Model IV	Step	34.974	6	0.000
	Block	166.458	13	0.000
	Model	166.458	13	0.000

The omnibus test examines how well the model performs. If the model's omnibus test p-value is less than 0.05, the model is regarded as significant; otherwise, it is insignificant. It is observed that the models' omnibus test p-values are lower than 0.05, implying that the models are well fitted to the data and the incorporated predictor variables are statistically significant.

Table 3. 12 Hosmer-Lemeshow tests for the models

	Chi-square	**df**	**Significance**
Model I	9.906	8	0.272
Model II	6.376	8	0.605
Model III	2.302	8	0.970
Model IV	1.134	8	0.997

The Hosmer-Lemeshow test shows the closeness of the forecasted values to actual values. If the Hosmer-Lemeshow p-value for the model is greater than 0.05, the response variable's actual and expected values are almost the same; otherwise, they are not very similar. Thus, the built model is well fitted to the data. The study discovers that the Hosmer-Lemeshow p-values for the models are greater than 0.05, indicating that they are a good fit to the data.

Table 3. 13 Cox and Snell R^2 and Nagelkerke R^2 values for the models

	-2 Log likelihood	**Cox and Snell R^2**	**Nagelkerke R^2**
Model I	97.844	0.393	0.618
Model II	75.785	0.460	0.722
Model III	45.757	0.538	0.845
Model IV	26.893	0.582	0.914

The Cox and Snell R^2 and Nagelkerke R^2 values show the soundness of the model and how much of the variance in the dependent variable is described by the model. Explicitly, the Cox and Snell R^2 and Nagelkerke R^2 values show that model I explains 39.30% and 61.80%, respectively, of the variance of the dependent variable. Thus, the covariates incorporated into model I explain between 39.30% and 61.80% of the dependent variable variance. Model II describes between 46.00% and 72.20% of the variance in the response variable, while Model III explains between 53.80% and 84.50% of the dependent variable variance. Lastly, model IV defines between 58.20% and 91.40% of the variance of the dependent variable. The Cox and Snell R^2 and Nagelkerke R^2 values indicate that the designed logit models are good.

3.5 Conclusions

This chapter analysed the default probability for private firms in a developing economy under distressed economic and financial conditions using stepwise logit models. The experiment's main focus was on the economic interpretation of the estimated coefficients of the predictor variables incorporated into the models. Using a unique data set of 191 defaulted and non-defaulted Zimbabwean private firms gathered from an anonymous major commercial bank over the observation period 2010 - 2018, the study found that a model that incorporates five accounting ratios combined with one firm characteristic and two macroeconomic variables best explains the likelihood that a Zimbabwean private firm will default. The study found the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the age of the firm, the real GDP growth rate and the inflation rate have a negative effect on the default probability, and the bank debt/total assets, earnings before interest and tax/total liabilities and accounts receivable/net sales ratios have a positive effect on the default probability.

The experimental results show that it is feasible to predict default probability for Zimbabwean private firms under distressed financial and economic conditions using accounting information. Although default detection models with firm and loan characteristics and financial ratios perform well in predicting the default of Zimbabwean private firms, the study provides evidence indicating that a default prediction model that supplements loan and firm characteristics and financial ratios with macroeconomic variables is associated with a superior in-sample classification rate of

98.40%. This finding indicates that the prediction ability of default models improves when macroeconomic factors are incorporated. Though the suggested model performs better than the other models studied, some issues exist for the extension of this study. The study may be extended by implementing a huge data set and analysing the in-sample and out-of-sample classification rates of the model(s). Further, more complex models such as artificial neural networks and support vector machines could be implemented, and more relevant predictor variables could be combined to improve the prediction capacity of the model. The analysis can also be extended to cover other financial products, such as mortgage loans, credit lines, and agricultural loans.

This current chapter examined the default probability of privately-traded firms without separating audited firms from unaudited ones. However, in chapter two, it was revealed that audited privately-held corporates and unaudited privately-owned corporations are dissimilar. Since audited and unaudited firms are not the same, combining them in the same data set may produce biased results. Therefore, the next chapter, chapter four, seeks to separately predict default probability for audited and unaudited Zimbabwean privately-owned firms under distressed economic and financial conditions using stepwise logit models based on different combinations of firm and loan characteristics, financial ratios and macroeconomic variables.

Chapter 4: Default prediction for audited and unaudited private firms under economic and financial stress: evidence from Zimbabwe

(*This chapter has been accepted for publication (in press) in the Afro-Asia Journal of Finance and Accounting (see Appendix A4.1))*

4.1 Introduction

Corporate failure is associated with high social and economic costs. Hence, corporate default prediction has received a lot of regulatory and scientific attention in the field of banking and finance. Statistical models have been in use in corporate financial distress prediction since the 1960s. Using accounting data in bankruptcy prediction, Beaver (1966) and Altman (1968) proposed univariate analysis and multiple discriminant analysis, respectively. Since the introduction of the Altman (1968) classical Z-score model, the detection of corporate default has become an area of active research.

Although much attention has been placed on corporate default prediction over the years, the majority of research has focused on default prediction models for listed corporates in developed economies for which reliable default data and information is widely available (Charalambakis and Garrett, 2019; Shumway, 2001; Beaver, 1966; Altman, 1968). Limited evidence has been dedicated to the drivers of default probability for private firms, of which the majority is devoted to advanced economies. Much less attention has been dedicated to the predictor variables of default probability for private firms in developing economies (see, for instance, Charalambakis and Garrett, 2019; Takahashi, Taques and Basso, 2018). Restricted research on the determinants of default probability for private corporations is due to the fact that the default data and information for private firms are not publicly available. Although it is tempting to apply models designed for advanced economies in undeveloped economies, the exercise does not always produce credible results (Ashraf, Felix and Serrasqueiro, 2019; Kliestik et al., 2018; Rylov, Shkurkin and Borisova, 2016), since the economic structures of these economies are considerably dissimilar (Rylov, Shkurkin and Borisova, 2016; Fedorova, Gilenko and Dovzhenko, 2013).

Examining the drivers of default probability for private corporations in undeveloped markets is vital. Private firms are the dominant corporate legal form in developing countries (Charalambakis and Garrett, 2019; Slefendorfas, 2016), possibly because of

the undeveloped local equity markets in these countries. Further, Charalambakis and Garrett (2019), Hyder and Lussier (2016), Organisation for Economic Co-operation and Development (2015), Charalambakis (2014), Halabi and Lussier (2014) and Wymenga et al. (2012) postulated that private corporates promote financial and technological innovations, reduce unemployment and encourage economic growth and development.

Private corporations are dissimilar to public firms; they are smaller in size, use more leverage, depend more on trade credit and bank loans, invest more and are characterised by high borrowing costs (see, for example, Gao, Hartford and Li, 2012; Michaely and Roberts, 2012). Non-stock-market predictors of default probability for private and public corporates are different (Charalambakis and Garrett, 2019). Using the same line of reasoning, Falkenstein, Boral, and Carty (2000) examined the credit risk for the United States (US) privately-owned companies and discovered that the association between credit risk and financial variables differs significantly across publicly traded and privately-owned corporates. In addition, private and public corporations are affected by diverse environmental and regulatory variables. Falkenstein, Boral and Carty (2000) argued that the economic import of this discovery is that default forecasting models founded on data pooled from public corporates and implemented on private corporates may probably misrepresent real default risk.

Charalambakis and Garrett (2019) stated that collecting default data and information for privately-owned corporates is challenging since their stocks are not traded on stock exchanges. Hence, records and financial statements of firm borrowers pooled from banks are the chief sources of default data and information for private corporations. Interestingly, Charalambakis and Garrett (2019) posited that it is imperative to forecast default probability for private corporations because it assists banks to formulate policies linked to the supply and cost of credit to private corporations. Further, the performance of private firm default prediction models provides more insights into the ability of financial ratios to forecast firm default.

Financial ratios used in private firm default prediction are extracted from audited and unaudited financial statements. In several jurisdictions, there are no legal requests for private corporations to divulge their financial results and produce audited financial statements even though some do (Minnis and Shroff, 2017). Of late, financial

institutions, especially commercial banks, have been demanding private corporates to submit audited financial statements before granting them loans and facilities. Although unaudited financial statements are cheaper and quicker to prepare than audited financial statements, in theory, they are more prone to creative accounting, errors, incorrect accounting procedures and fraud. Cenciarelli, Greco and Allegrin (2018) and Gul, Zhou and Zhu (2013) proffered that corporations with audited financial statements pose a lower default risk to creditors than their unaudited counterparts.

General macroeconomic conditions have a significant impact on corporate default probability. Distressed financial and economic conditions are characterised by high default rates (Charalambakis and Garrett, 2019). Basel II/III Advanced Ratings-based (AIRB) approach and International Financial Reporting Standard 9: Financial Instruments (IFRS 9) emphasise the imperativeness of implementing new models that properly link default probabilities to macroeconomic variables. Stressed default probabilities are crucial in credit risk management. For instance, they are used as inputs in the determination of conditional expected credit losses under stress tests. The incorporation of macroeconomic variables improves the prediction results of private corporate default detection models (Charalambakis and Garrett, 2019). Nevertheless, the predicament is that there is lack of consensus in industry on which macroeconomic variables have the most significant influence on default risk for private corporations under downturn conditions, resulting in the creation of different default probability forecasting models.

Against this backdrop, this study develops stepwise logistic regression models based on different combinations of firm and loan characteristics, financial ratios and macroeconomic variables to separately examine the drivers of default probability for audited and unaudited Zimbabwean privately-owned firms under distressed economic and financial conditions twelve months in advance. Hayden (2011) and Basel Committee on Banking Supervision (1999) stated that a twelve-month period allows financial institutions to pursue corrective actions to circumvent projected defaults and guarantees that timely data is included in the rating techniques. The main aim of this study is on the identification and economic interpretation of the forecasted coefficients for the drivers included in the developed models. For relevance and effectiveness reasons, the study applies two unique cross-sectional real-world data sets of defaulted and non-defaulted loan accounts for 308 audited and 301 unaudited private firms

gathered from a major anonymous Zimbabwean commercial bank over the sample period from 2010 to 2018. Geographically, the sample data sets are an accurate depiction of the Zimbabwean market.

Zimbabwe offers an interesting and challenging case study in examining default risk for private corporations in developing economies. It has witnessed severe and extended distressed economic and financial conditions that have promoted significant informalisation and deindustrialisation in the country over the past two decades. In order to fix the economy, the government adopted several currencies that included the South African rand, euro, Botswana pula, British pound and American dollar, and phased out the Zimbabwean dollar in 2009. Nevertheless, the American dollar emerged as a major currency and has been used as the functional and presentation currency for companies. Masiyandima et al. (2018) propounded that the emergence of the American dollar as the major currency led to negative and low inflation rates, which adversely impacted the country's growth. Zimbabwe observed twenty-eight successive months of deflation from October 2014 to January 2017 (Masiyandima et al., 2018). During the observation period, World Bank Group (2020a) indicated that the real GDP growth rate fell from more than 10% per annum in 2010 - 2012 to 2% in 2013, improving to 2.4% in 2014, dropping to 1.8% in 2015 to 0.7% in 2016 before recuperating to 4.7% in 2017 and deteriorating to 3.5% in 2018. The distressed economic and financial conditions observed in Zimbabwe are seldom found in developed economies or even in some undeveloped markets.

In order to empower indigenous people, the Zimbabwean government endorsed the Indigenisation and Economic Empowerment Act into law on April 17, 2008. Section 3(1) of the Act obliges foreign-owned businesses with an asset value of US$ 500 000 or more to cede at least 51% of their shares to indigenous Zimbabweans. As a result, the majority of Zimbabwean private corporations are owned by indigenous people, most of whom have limited or inappropriate industry experience and restricted managerial skills. Compared to Zimbabwean public corporations, Zimbabwean private firms are often undercapitalised (resulting in them using more debt), depend more on trade credit and bank loans, invest more and are linked with higher borrowing costs (due to their low creditworthiness).

The Zimbabwean banking sector is regulated and supervised by the Reserve Bank of Zimbabwe (RBZ). As of December 31, 2018, 13 commercial banks, 1 savings bank, 5 building societies, 2 development financial institutions, 6 deposit-taking microfinance institutions (MFIs) and 199 credit-only MFIs were operating in Zimbabwe. With special reference to total deposits, total assets, and total loans and advances, commercial banks have been dominating the Zimbabwean banking sector. Reserve Bank of Zimbabwe (2018) showed that commercial banks were accountable for, as of December 31, 2018, 83.74% of total assets, 84.44% of total deposits and 68.71% of total loans. The ownership of commercial banks is spread between foreigners, government and local individuals and companies. World Bank (2020) specified that foreign-owned banks constituted 38% of all Zimbabwean banks in 2013. Zimbabwean commercial banks are in the process of effecting Basel II rules in order to align themselves with global regulatory standards. The RBZ is leading the Basel II implementation process. Nevertheless, some banks, mostly government-owned and local banks do not possess adequate technical capacity to adopt Basel II/III principles properly.

This study offers substantial evidence indicating that models including firm and loan characteristics, macroeconomic factors and accounting ratios best explain the default probability for audited and unaudited Zimbabwean private firms. These models are associated with the superior in-sample classification rates. In particular, the study finds a negative effect of the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate, the inflation rate and the net sales/net sales last year ratio and a positive effect of the bank debt/total assets, earnings before interest and tax/total liabilities, short-term debt/total assets and current assets/total assets ratios on the default probability for audited Zimbabwean private corporations. On the other hand, the study discovers a negative effect of the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate and the inflation rate, and a positive effect of the earnings before interest and tax/total liabilities, short-term debt/total assets, net sales/net sales last year and current assets/total assets ratios and the interest rate on the default probability for unaudited Zimbabwean private corporates.

The results of the study provide compelling evidence showing that accounting information is crucial in separating defaulted private firms from non-defaulted ones under downturn conditions. The nominated input financial ratios are imperative because they represent some of the most important credit risk drivers, including, profitability, leverage, growth and liquidity. Also, this study indicates that the inclusion of macroeconomic variables improves model fit and the prediction performance of the default models. In line with this finding, Sheikh and Yahya (2015) and Hill, Perry and Andes (2011) indicated that the prediction results of bankruptcy forecasting techniques are improved by incorporating macroeconomic factors. This implies that firm-and-loan-characteristics, accounting-data and macroeconomic-information based models best explain the default probability for audited and unaudited Zimbabwean private firms. Further, the study reveals that the drivers of default risk for audited and unaudited Zimbabwean private firms are not the same.

The rest of the chapter is designed as follows: section 4.2 outlines the literature review and section 4.3 presents a brief overview of the methodology. In section 4.4, data and variables are described and section 4.5 is allocated to experimental results. Section 4.6 presents the discussion of results and section 4.7 outlines the robustness checks for the designed models. Section 4.8 concludes the analysis, provides the implications of the study and presents potential directions for future research.

4.2 Literature review

Since the introduction of the Altman (1968) classical Z-score model, the prediction of default probability has become an area of extensive research. A myriad of models has been generated to try not only to categorise a corporate as healthy or not but also to convey the outcome in terms of the probability of default premised on the features of the sample of companies adopted in model designing (Altman, 2018). These models include logit models (Martin, 1977), contingent-claim techniques (Merton, 1974), probit models (Zmijewski, 1984), expert systems (Gherghina, 2015), neural networks (Abedin et al. 2018; Guotai, Abedin and Moula, 2017), support vector machines (Abedin et al. 2018; Moula, Guotai and Abedin, 2017), genetic algorithms (Zelenkov, Fedorova and Chekrizov, 2017), recursive partitioning (Frydman, Altman and Kao, 1985), hazard models (Gupta, 2017) and machine learning methods (Barboza, Kumar and Altman, 2017), among others. Martin (1977) pioneered the application of logit

analysis in examining corporate bankruptcy by forecasting bank failure and Ohlson (1980) became the first author to implement a logit model to analyse bankruptcy for non-financial sector corporates.

Although corporate default prediction has been receiving much attention in risk management, most studies focus on public firms in developed economies (Bauer and Agarwal, 2014; Tinoco and Wilson, 2013; Agarwal and Taffler, 2008; Shumway, 2001). Corporate default forecasting literature for developing economies (Kwak, Shi and Kou, 2012) and for privately-owned companies (Charalambakis and Garrett, 2019) is generally restricted. Limited evidence on private firm default prediction is substantially dedicated to advanced markets (Diekes et al., 2013; Cangemi, Servigny and Friedman, 2003; Falkenstein, Boral and Carty, 2000). Nevertheless, applying models designed for advanced countries to emerging economies does not always produce plausible results (see, Ashraf, Felix and Serrasqueiro, 2019) due to the fact that the economic structures of developed and undeveloped economies are considerably different (Liang, Tsai, and Wu, 2015; Fedorova, Gilenko and Dovzhenko, 2013). For instance, developing economies depend on primary commodity exports to generate foreign currency and they bank on imports for some basic food supplies and energy. Therefore, developing countries are exposed to more challenges when dealing with booms originating from commodity price surges and exogenous shocks which seem insignificant but habitually lead to high corporate default rates in undeveloped markets. Due to these structural differences, developing economies are characterised by limited historical statistical data, closed markets, institutional and legal barriers and reduced predictive power of market signals (Rylov, Shkurkin and Borisova, 2016), which affect how corporate default probability is modelled. Moreover, Waqas and Md-Rus (2018) argued that it is important to recognise that advanced economies are associated with clearer bankruptcy laws and procedures than undeveloped economies. In the same vein, Altman (2018), Takahashi, Taques and Basso (2018) and Slefendorfas (2016) pronounced that each country has unique characteristics, and consequently models created explicitly for individual economies outperform general models.

Hayden (2011) propounded that the forecasting capability of statistical techniques is premised on the presumption that the past association between the predictor variables of the developed model and the default event will remain the same in the future.

However, this supposition may not remain unchanged over long periods given a wide range of possible events that can take place in financial markets, for example, changes in accounting policies of companies, financial and economic crises and the introduction of regulatory documents. (Takahashi, Taques and Basso, 2018; Singh and Mishra, 2016; Smaranda, 2014; Hayden, 2011). Owing to changes in time horizons, financial situations and economic conditions, the applicability and predictive performance of the existing default detection techniques under new settings is a practical inquiry that needs to be addressed in modern finance (Altman, 2018; Timmermans, 2014). Takahashi, Taques and Basso (2018), Smaranda (2014) and Hayden (2011) revealed that it is necessary to regularly re-validate and re-calibrate the bankruptcy forecasting models in the wake of new events in order to guarantee that their detection capacity does not decrease. Further, Sign and Mishra (2016) re-estimated the Z-score (Altman, 1968), Y-score (Ohlson, 1980), and X-score (Zmijewski, 1984) models and posited that the coefficients of these models are responsive to time horizons and changes in financial situations.

Charalambakis and Garrett (2019) collecting default data and information for private corporations is a difficult task because their shares are not bought and sold on stock exchanges. Therefore, financial statements and records of firm borrowers pooled from banks are the main sources of default data and information for private corporations. Accounting information used in detecting default probability for private firms is derived from audited and unaudited financial statements. In several economies, there are no legal demands for privately-owned corporates to disclose their financial results and generate audited financial statements even though some do (Minnis and Shroff, 2017). Bratten et al. (2013) and Minnis (2011) proffered that audited financial records guarantee that there are no material mistakes or misstatements in the results. Further, Bratten et al. (2013) and Dechow, Ge and Schrand (2010) posited that by reducing the misrepresentations of financial records, a credible audit guarantees reliable financial reporting.

Auditors perform information and insurance roles. Investors believe that companies audited by huge firms have plausible earnings and are less risky. Accordingly, audited corporates benefit from low-interest rates on borrowed funds and low returns anticipated by investors (Cenciarelli, Greco and Allegrin, 2018). Huq, Hartwig and Rudholm (2018), Cassar (2011) and Minnis (2011) posited that firms that present

audited financial statements to creditors are characterised by lower costs of debt than corporates that do not. The cost of debt indicates the probability of default associated with the borrower. Corporates with high cost of debt are associated with high default risk, and those with low cost of debt are characterised by low default risk. Consequently, Cenciarelli, Greco and Allegrin (2018) and Gul, Zhou and Zhu (2013) indicated that corporations with audited financial statements pose lower default risk to creditors than their unaudited counterparts. Further, Cenciarelli, Greco and Allegrin (2018) posited that auditing firms can avert corporate bankruptcies. They can address the issues related to accounting frameworks' inadequacies and financial regulations' mediocrity. Inadequate accounting frameworks, mediocre financial regulations and suboptimal productivity are some of the major causes of corporate failure (Jahur and Quadir, 2012). Cenciarelli, Greco and Allegrin (2018) and references therein argued that big auditing firms have the skills and prowess to analyse bankruptcy and advise firms on how to deal with it. Based on the examination of the financial ratios, Hamzani and Achmad (2018) proposed that small-to-medium enterprises (SMEs) complying with the accounting standards have higher profitability than their non-complying counterparts. Given that profitability is negatively associated with bankruptcy, the finding of Hamzani and Achmad (2018) seems to support the supposition that audited firms are associated with low rates of default.

Since the economic downturns are associated with high default frequencies (see, for example, Mihalovic 2016; Canals-Cerda and Kerr, 2015a; Leow and Crook, 2014), the AIRB approach and IFRS 9 provide new impetus for banks to design new default detection models under distressed economic and financial conditions (see International Accounting Standards Board 2014; Basel Committee on Banking Supervision, 2011, 2006). Jensen, Lando and Medhat (2017) further stated that a private firm default model premised on only firm-specific factors is not proficient in describing the cyclical nature of the witnessed defaults. Using Cox models, Jensen, Lando and Medhat (2017) posited that macroeconomic factors and accounting ratios are crucial in default forecasting for Danish privately-owned firms. The authors proposed that the effects of firm-specific factors remain robust to the addition of the macroeconomic variables. Charalambakis and Garrett (2019), Crook and Bellotii (2013) and Bellotii and Crook, (2009) observed that the inclusion of macroeconomic factors improves the model fit and the forecasting ability of default models.

4.3 Methodology

Beaver, Correia and McNichols (2012) and Beaver, McNichols and Rhie (2005) articulated that the forecasting ability of standard accounting-based bankruptcy models has been declining over the years. A number of studies, including Beaver, Correia and McNichols (2012) and Agarwal and Taffler (2008) posited that supplementary explanatory variables need to be incorporated in the bankruptcy prediction models. Sun, Huang and He (2014) proffered that it is essential to disrupt the traditional perspective of implementing quantitative models founded solely on financial variables and apply non-financial information to broaden the research work on bankruptcy prediction. Altman (2018), Gupta, Gregoriou and Healy (2015) and Altman, Sabato and Wilson (2010) suggested that non-financial variables improve the predictive power of bankruptcy forecasting models. Further, Jensen, Lando and Medhat (2017) noted that a private firm default model based on only firm-specific variables is not capable of assessing the cyclical nature of the observed defaults. Macroeconomic variables and accounting ratios are fundamental in default prediction for privately-traded corporates (Jensen, Lando and Medhat, 2017). Jensen, Lando and Medhat (2017) argued that the effects of firm-specific variables stay robust to the addition of the macroeconomic factors. Interestingly, Charalambakis and Garrett (2019) and Charalambakis (2014) indicated that the forecasting capability of private firm bankruptcy models is improved by combining financial ratios with firm and loan features and macroeconomic factors.

Literature revealed that firms with audited financial statements pose a lower default risk to creditors than their unaudited counterparts (Cenciarelli, Greco and Allegrin, 2018 and Gul, Zhou and Zhu, 2013). Therefore, from a risk management perspective, it is vital to separately design models for and examine drivers of default probability for audited and unaudited private corporations. This study proposes stepwise logistic regression models based on different combinations of firm and loan features, financial ratios and macroeconomic factors to separately examine the drivers of default probability for audited and unaudited Zimbabwean privately-traded corporates under downturn conditions twelve months in advance.

In designing corporate default prediction models, logit models are the most popular statistical models in practice and in the academic literature as well (Becerra-Vicario et al., 2020; Durica, Valaskova and Janoskova, 2019; Altman et al., 2017; Kovacova and

Kliestik, 2017; Mendelova and Stachova, 2016; Hayden, 2011). Hayden (2011) argued that the logit model is the most prevalent model because its output can be simply inferred as default probability and it allows a simple check of the economic significance of the empirical dependence between the default risk and the potential explanatory variables. Becerra-Vicario et al. (2020), Durica, Valaskova and Janoskova (2019), Altman et al. (2017), Kovacova and Kliestikova (2017) and Bateni and Asghari (2016) suggested that logistic regression has been expansively implemented in corporate default forecasting mainly due to its ease-to-use nature, reliability and high classification rate. Logistic regression is flexible when implementing real-world data because it does not assume normal distribution, linearity and independence among independent covariates (Durica, Valaskova and Janoskova, 2019; Kliestik, Kocisova and Misankova, 2015). Also, Durica, Valaskova and Janoskova (2019), Obradovic et al. (2018), Kliestik, Kocisova and Misankova (2015) and Kliestik et al. (2014) indicated that logistic regression has less restrictive statistical requirements than other statistical models such as multiple discriminant and probit models. Therefore, a logistic regression model precisely describes in a simple way the behaviour of default probability.

Corporate default is a dichotomous variable. Thus, a binary stepwise logistic regression model is applied to forecast the probability of default, that is, the default probability only takes two values, 1 if default happens and 0 if default does not happen. The probability of default, $P_i(z)$, is given by

$$P_i(z) = \frac{\exp(z_i)}{1+\exp(z_i)},$$

where, for the *i*th account, z_i is the dependent variable given a particular set of predictors. Here, z_i is described by

$$z_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \mu_i,$$

where, β_1, β_2, ..., β_k denote regression coefficients, β_0 is the intercept, x_1, ..., $x_k$epitomise k covariates (i.e., financial ratios, firm and loan characteristics, and macroeconomic variables) and μ_i represents the error term. Macroeconomic variables and financial ratios are involved with a time lag of twelve months.

In this study, the omnibus tests, pseudo R^2 measures (i.e., Cox and Snell R2 and Nagelkerke R^2) and Hosmer-Lemeshow tests are applied to examine the robustness of the developed models.

4.4 Data and variables

Two unique cross-sectional real-world data sets of defaulted and non-defaulted loan accounts for audited and unaudited private firms gathered from an anonymous major Zimbabwean commercial bank over the sample period from 2010 to 2018 are used to fit the stepwise logistic regression models. Account default refers to a situation where an obligor is not likely to settle its credit obligations or past due more than 90 days on any substantial credit obligation (Crook and Bellotti, 2013; Basel Committee on Banking Supervision, 2006). Data set I consists of defaulted and non-defaulted loans accounts for audited private corporates, while data set II contains defaulted and non-defaulted loan accounts for unaudited private corporations. Initially, data set I comprises 315 audited private firm loan accounts and data set II encompasses 309 unaudited private corporate loan accounts. The data sets are cleaned to get rid of all general errors. Government-owned companies, financial institutions and multinational corporations which do not reflect the classical features of typical Zimbabwean privately-traded firms are excluded from the samples. Loan accounts are observed and tracked yearly. Financial statements covering periods of less than a year, entries recorded more than once in the data matrices and loan accounts whose default information and audit status are unknown or debatable are removed from the samples.

Therefore, the study guarantees that the

(i) financial statement data of sample corporates is valid, and henceforth, default analysis is objective;

(ii) sample data is free from general errors;

(iii) data sets are made up of only homogeneous observations, and as a result, the association between the covariates and the default event is comparable;

(iv) default event adopted in developing the logit models is similar to the default event the designed models can forecast; and

(v) the default and audit status information is available and dependable for all obligors.

After data cleaning, 308 audited companies (i.e., 44 defaulted and 264 non-defaulted) and 301 unaudited firms (i.e., 98 defaulted and 203 non-defaulted) are left in the final samples. The unequal distribution of defaulted and non-defaulted corporates in the data sets adopted in this analysis is in line with that in the existent research literature (see Sabela et al., 2018). This experiment follows a two-step approach in selecting dependable, relevant and precise predictor variables. The study adopts, in the first step, drivers that are popular in academic literature, relevant to the experiment and have superior predictive power in empirical researches, intending to improve the predictive abilities of the developed models. In the second step, the study implements a stepwise selection technique with forward elimination to choose the most statistically significant drivers of default probability. The initial set of the predictors of default probability has twenty financial ratios (Table 4.1), six firm and loan characteristics (Table 4.2) and six macroeconomic factors (Table 4.3).

The last set of financial statements filed a year before default by defaulted firms is examined in computing their respective financial ratios since a modelling or forecast horizon is set at one year. This modelling horizon is long enough to permit banks to take some corrective action to prevent forecasted defaults and short enough to warranty the aptness of the data input into the rating model (see, for instance, Hayden 2011 and Basel Committee on Banking Supervision, 1999). In calculating financial ratios for non-defaulted firms, their latest filed financial statements are analysed since they give the most current financial position of the firms. Firm and loan characteristics are collected at the time of loan application. Macroeconomic variables, lagged twelve months before default, are obtained from the World Bank Group. Tables 4.1 - 4.3 also show the anticipated associations involving the predictor variables and the probability of default. A positive sign (+) shows that if the value of the predictor variable rises, the probability of default increases. Contrariwise, a negative sign (-) indicates that if the value of the driver increases, the probability of default decreases.

Table 4. 1 Financial ratios

Abbreviation	Financial ratio	Risk factor	Expected effect	Source
TL/TA	Total liabilities/total assets	Leverage	+	Becerra-Vicario et al. (2020)
EQ/TA	Equity/total assets	Leverage	-	Hayden (2011)
BD/TA	Bank debt/total assets	Leverage	+	Hayden (2011)
SD/TA	Short-term debt/total assets	Leverage	+	Hayden (2011)
CA/CL	Currents assets/current liabilities	Liquidity	-	Ogachi et al. (2020)
AR/NS	Accounts receivable/net sales	Activity	+	Hayden (2011)
AP/NS	Accounts payable/net sales	Activity	+	Hayden (2011)
(NS-MC)/PC	(Net sales – material costs)/ personnel costs	Productivity	-	Hayden (2011)
NS/TA	Net sales/total assets	Turnover	-	Hayden (2011)
EBIT/TA	Earnings before interest and tax/ total assets	Profitability	-	Stefko, Horvathova and Mokrisova (2020)
OBI/TA	Ordinary business income/ total assets	Profitability	-	Hayden (2011)
TA	Total assets	Size	-	Charalambakis and Garrett (2019)
(CA-CL)/TA	(Current assets – current liabilities)/ total assets	Liquidity	-	Durica, Valaskova and Janoskova (2019)
EBIT/EQ	Earnings before interest and tax/ equity	Profitability	-	Charitou, Neophytou and Charalambous (2004)
NS/NSLY	Net sales/net sales last year	Growth	-/+	Hayden (2011)
TL/TLLY	Total liabilities/ total liabilities last year	Leverage growth	+	Hayden (2011)
EBIT/TL	Earnings before interest and tax/ total liabilities	Leverage	-	Wang (2011)
CL/TA	Current liabilities/total assets	Leverage	+	Al-Kassar and Soileau (2014)

TL/EQ	Total liabilities/equity	Leverage	+	Gallo (2015), Keener (2013)
CA/TA	Current assets/total assets	Liquidity	-	Durica and Svabova (2019).

Several ratios (such as the current liabilities/total assets and current assets/total assets ratios) show varied financial characteristics of borrowers that are crucial in modelling probability of default under distressed economic and financial conditions. The analysis also includes dynamic ratios that relate current to past levels of specific balance sheet entries, for example, the ratio of total liabilities/total liabilities last year. Hayden (2011) articulated that dynamic ratios are critical in detecting default probability. Financial ratios adopted in this analysis denote significant drivers of default risk, that is, leverage growth, leverage, profitability, liquidity, productivity, turnover, growth, activity and firm size.

Table 4. 2 Firm and loan characteristics

Abbreviation	Variable	Expected effect	
LN	Loan amount	+	Bohorquez, Matienzo and Olivares (2013)
INT	Interest rate	+	Michalkova, Adamko and Kovacova (2018)
AG	Age of the firm	-	Succurro (2017)
CTV	Collateral value	-	Bauer and Edresz (2016); Bohorquez, Matienzo and Olivares (2013)
TwB	Time with the bank	-	Jensen, Lando and Medhat (2017)
LMP	Loan maturity period	+	Bohorquez, Matienzo and Olivares (2013)

Private firm loans mentioned here are commercial loans not including credit lines and mortgage loans. The loan amount is the original loan amount granted to the corporate borrower and the interest rate is the initial contractual lending interest rate associated with the loan. Firm age denotes the age of the firm in years since the time of its incorporation to the time of loan application. Collateral value represents the value of collateral lodged by the firm client at the time of getting a loan. Kinds of collateral include land, equipment, residential real estate and commercial real estate, but disregard personal guarantees. The time with the bank is the number of years the firm borrower has been in a business relationship with a bank as its lender. Finally, the loan maturity period represents the term in years of the loan granted.

Table 4. 3 Macroeconomic factors

Abbreviation	Variable	Expected effect	Source
GNIC	Gross national income per capita growth	-	-
RGDP	Real GDP growth rate	-	Charalambakis and Garrett (2019), Jensen, Lando and Medhat (2017)
INF	Inflation rate (% yearly average)	+	Rezende et al. (2017)
BB	Budget balance (% GDP)	+	-
PDE	Public debt (% GDP)	+	-
UR	Unemployment rate	+	Korol (2017)

Missing data may compromise inferences. Thus, missing data need to be appropriately handled. In this study, observations with missing data are not excluded from the samples. Mean imputation of missing values is adopted in this experiment in order to diminish bias and escalate accuracy. Song and Shepperd (2007) propounded that mean imputation maintains the sample size and is easy to understand and apply. Under this approach, the average of the non-missing values for each driver of probability default with missing value(s) is calculated. Each missing value is then substituted with the computed average. In the data set I, the ordinary business income/total assets ratio and the ratio of accounts payable/net sales are each missing 0.32% of their values, translating into 0.65% corporations with missing values. It is perceived that 2.27% and 0.38% of defaulted and non-defaulted audited firms, respectively, have missing values. In the data set II, the ratio of short-term debt/total assets, the ordinary business income/total assets ratio, the ratio of accounts payable/net sales and the interest rate are each missing 0.33% of their values, transforming into 0.66% corporates with missing values. It is observed that 1.02% and 0.49% of defaulted and non-defaulted unaudited firms, respectively, have missing values. The study concludes that missing values are more common for defaulted companies than for non-defaulted corporates in both audited and unaudited firm data sets. Outliers can considerably bias the calculated

model parameters and result in inappropriate inferences. The study winsorizes extreme values at the distribution's 1st and 99th percentiles to avoid removing the outliers from the samples.

Tables 4.4 - 4.6 summarise the descriptive statistics for financial ratios, firm and loan characteristics and macroeconomic factors, respectively, for the whole sample of audited private firms.

Table 4. 4 Financial ratios for audited firms with descriptive statistics

Variable	Min	Max	Mean	SD
TL/TA	0.03	1.41	0.68	0.34
EQ/TA	-0.13	0.97	0.36	0.29
BD/TA	0.00	0.41	0.09	0.10
SD/TA	0.00	0.82	0.15	0.18
CA/CL	0.41	3.90	1.35	0.84
AR/NS	0.01	1.53	0.21	0.29
AP/NS	0.00	0.84	0.18	0.20
(NS-MC)/PC	-1.57	5.92	1.89	1.82
NS/TA	0.11	4.56	1.95	1.39
EBIT/TA	-0.48	0.40	0.07	0.15
OBI/TA	0.11	5.15	2.40	1.78
TA*	3.13	149.15	23.06	38.15
(CA-CL)/TA	-0.54	0.97	0.09	0.32
EBIT/EQ	-3.47	4.69	0.12	1.35
EBIT/TL	-0.53	2.57	0.27	0.57
CL/TA	0.02	1.19	0.57	0.33
TL/EQ	-3.40	5.15	2.09	2.07
CA/TA	0.10	1.00	0.66	0.29
NS/NSLY	0.40	3.42	1.27	0.74
TL/TLLY	0.39	4.95	1.39	0.94

SD denotes standard deviation. * In millions of US dollars.

Table 4.4 presents the minimum, maximum, mean and standard deviation values for the financial ratios based on the whole sample of audited privately-owned corporates.

Table 4. 5 Firm and loan characteristics for audited firms with descriptive statistics

Variable	Min	Max	Mean	SD
LN*	0.16	10.00	1.65	2.07
INT	5.00	22.00	13.91	3.84
AG	2.00	79.00	17.36	14.21
CTV*	0.00	6.27	0.64	1.20
TwB	1.00	15.00	5.96	4.30
LMP	1.00	5.00	1.14	0.74

SD denotes standard deviation. * In millions of US dollars.

Table 4.5 outlines the minimum, maximum, mean and standard deviation values for the firm and loan characteristics based on the entire sample of audited privately-traded corporates.

Table 4. 6 Macroeconomic factors for audited firms with descriptive statistics

Variable	Min	Max	Mean	SD
GNIC	-1.50	20.70	5.74	7.21
RGDP	0.70	19.70	6.04	6.89
INF	-2.40	10.60	0.82	3.02
BB	-11.20	-1.10	-2.38	2.50
PDE	37.10	54.20	43.84	6.92
UR	4.90	5.60	5.38	0.21

SD denotes standard deviation.

This table reports the minimum, maximum, mean and standard deviation values for the macroeconomic factors based on the entire audited private firm sample.

Tables 4.7 - 4.9 outline the descriptive statistics for financial ratios, firm and loan characteristics and macroeconomic variables, respectively, for the entire sample of unaudited private firms.

Table 4. 7 Financial ratios for unaudited private firms with descriptive statistics

Variable	Min	Max	Mean	SD
TL/TA	0.03	1.61	0.74	0.38
EQ/TA	-0.13	0.99	0.42	0.29
BD/TA	0.00	0.23	0.09	0.07
SD/TA	0.00	0.82	0.15	0.16
CA/CL	0.45	11.32	1.71	2.02
AR/NS	0.01	0.59	0.15	0.12
AP/NS	0.01	0.84	0.13	0.16
(NS-MC)/PC	1.15	11.87	5.52	3.77
NS/TA	0.09	9.09	2.02	2.50
EBIT/TA	-0.48	0.40	0.07	0.13
OBI/TA	-0.56	9.05	1.98	2.62
TA*	0.15	2650.56	85.83	397.46
(CA-CL)/TA	-0.53	0.97	0.10	0.29
EBIT/EQ	-6.05	10.85	0.22	1.99
EBIT/TL	-0.53	2.57	0.22	0.47
CL/TA	0.02	1.00	0.49	0.30
TL/EQ	0.03	7.84	2.68	2.63
CA/TA	0.06	1.19	0.59	0.33
NS/NSLY	0.33	6.58	2.34	2.17
TL/TLLY	0.39	9.16	1.93	2.09

SD denotes standard deviation. * In millions of US dollars.

Table 4.7 presents the minimum, maximum, mean and standard deviation values for the financial ratios based on the sample of unaudited privately-owned firms.

Table 4. 8 Firm and loan characteristics for unaudited firms with descriptive statistics

Variable	Min	Max	Mean	SD
LN*	0.16	10.00	1.97	2.16
INT	5.00	24.00	14.76	5.02
AG	1.00	85.00	17.81	14.56
CTV*	0.00	8.00	1.20	2.03
TwB	1.00	15.00	6.84	4.18
LMP	1.00	5.00	1.12	0.62

SD denotes standard deviation. * In millions of US dollars.

Table 4.8 outlines the minimum, maximum, mean and standard deviation values for the firm and loan characteristics based on the entire sample of unaudited private corporations.

Table 4. 9 Macroeconomic factors for unaudited firms with descriptive statistics

Variable	Min	Max	Mean	SD
GNIC	-1.50	20.70	5.64	7.59
RGDP	0.70	19.70	6.11	6.93
INF	-2.40	10.60	0.75	3.21
BB	-11.2	-1.10	-2.65	2.79
PDE	37.10	54.20	44.03	6.55
UR	4.90	5.60	5.35	0.22

SD denotes standard deviation.

This table reports the minimum, maximum, mean and standard deviation values for the macroeconomic factors based on the entire unaudited private firm sample.

4.5 Empirical results

4.5.1 Model fit

The entire samples of audited and unaudited private firms are used to fit the models. Due to their small sizes, samples are not split into test samples and validation samples since it may introduce bias (see, for instance, Xu and Goodacre, 2018). To choose the most statistically significant drivers of default probability, the experiment adopts a stepwise forward technique at a 90% level of confidence. The probability needed for a risk factor to be incorporated into the regression equation is placed at 0.15, while the probability required for a risk factor to be excluded from the regression equation is set at 0.20. This stepwise threshold incorporates all statistically significant covariates related to the response variable (Hosmer and Lemeshow, 2000). To deal with the challenge of multicollinearity, given two greatly correlated covariates, one of them is excluded from the model(s). Using diverse amalgamations of firm and loan characteristics, financial ratios and macroeconomic factors, the study proposes four stepwise logistic regression models as follows: model I: model I incorporates financial ratios and firm and loan characteristics to analyse default risk for audited private firms; model II: model II includes financial ratios, firm and loan characteristics and macroeconomic factors to examine probability of default for audited private corporates; model III: model III incorporates financial ratios and firm and loan characteristics to predict probability of default for unaudited private companies; and model IV: model IV includes financial ratios, macroeconomic variables and firm and loan characteristics to forecast probability of default for unaudited private corporations.

4.5.2 Predictive ability of the logit models

The predictive performance evaluation of default models plays an imperative role in the designing of modelling frameworks. In this analysis, the 2 x 2 classification matrix (see, Table 4.10) which reveals the following four outcomes is employed to describe the performance of the models.

(i) True positive (TP): class of a defaulted firm correctly selected as a defaulted firm.

(ii) False positive (FP): category of a non-defaulted firm wrongly chosen as a defaulted firm.

(iii) False negative (FN): class of a defaulted firm wrongly pinpointed as a non-defaulted firm.

(iv) True negative (TN): category of a non-defaulted firm rightly identified as a non-defaulted firm.

Table 4. 10 The 2 x 2 classification matrix for a classification problem

	Predicted observations		
	Predicted negative	**Predicted positive**	
Actual observations			
Actual negative	TN	FP	**ON**
Actual positive	FN	TP	**OP**
	PN	**PP**	**TOTAL**

ON (observed negative) is equal to FP + TN. OP (observed positive) is equal to TP + FN. PN (predicted negative) is equal to FN + TN. PP (predicted positive) is equal to TP + FP. TOTAL (total number of observations) is equal to TP + FP + FN + TN.

This experiment employs the in-sample classification rate and type I and type II error rates to assess the models' performance. The classification rate shows the proportion of corporations forecasted properly. Type I error rate is the probability of classifying non-defaulted firms as defaulted, while type II error rate refers to the probability of categorising defaulted firm obligors as non-defaulted. The classification rates and type I and type II error rates for the designed stepwise logistic regression models are determined for cut-off points from 0.1 to 0.9 at 10% significance level. These performance metrics are determined as follows:

$$\text{classification rate} = \frac{\text{TP+TN}}{\text{TOTAL}},$$

$$\text{type I error rate} = \frac{\text{FP}}{\text{FP+TN}},$$

$$\text{type II error rate} = \frac{\text{FN}}{\text{FN+TP}}.$$

4.5.2.1 Model I

Table 4.11 outlines the in-sample classification rates and type I and type II error rates for model I.

Table 4. 11 Cut-off points, classification rates and type I and type II error rates for model I

Cut-off point	Classification rate (%)	Type I error rate (%)	Type II error rate (%)
0.1	89.30	12.50	0.00
0.2	89.30	12.50	0.00
0.3	92.90	8.33	0.00
0.4	92.90	8.33	0.00
0.5	89.30	4.17	50.00
0.6	89.30	4.17	50.00
0.7	85.70	4.17	75.00
0.8	82.10	4.17	100.00
0.9	85.70	0.00	100.00

The in-sample classification rates for model I range from 82.10% to 92.90%. Type I error rates are confined between 0% and 12.50%, while type II error rates run from 0% to 100%. The existent literature proposed several ways of selecting optimal cut-off points (see, for instance, Sabela et al., 2018 and references therein). This research chooses cut-off points at which the sum of type 1 and type II error rates is minimal and the overall performance of the model is high as the optimal cut-off points. In this case, the cut-off points of 0.3 and 0.4 are associated with the minimal sum of the two errors, 8.33% + 0% (8.33%) and a high model in-sample classification rate of 92.90%. Hence, to optimise model I, the cut-off points of 0.3 and 0.4 are selected as the optimal cut-off points.

4.5.2.2 Model II

Table 4. 12 Cut-off points, classification rates and type I and type II error rates for model II

Cut-off point	Classification rate (%)	Type I error rate (%)	Type II error rate (%)
0.1	71.40	29.17	25.00
0.2	78.60	20.83	25.00
0.3	92.90	4.17	25.00
0.4	92.90	4.17	25.00
0.5	96.40	0.00	25.00
0.6	92.90	0.00	50.00
0.7	85.70	0.00	100.00
0.8	85.70	0.00	100.00
0.9	85.70	0.00	100.00

Table 4.12 indicates that the in-sample classification rates for model II span from 71.40% to 96.40%. Type I error rates stretch from 0% to 29.17%, while type II error rates swing from 25.00% to 100%. The cut-off point of 0.5 is selected as the optimal cut-off point, since it is associated with the minimal sum of the two errors (25.00%) and a high model in-sample classification rate of 96.40%. Interestingly, model I has an in-sample classification rate of 92.90%, while model II has an in-sample classification rate of 96.40%, indicating that the inclusion of macroeconomic variables improves the predictive capacity of the default models for audited Zimbabwean private firms.

4.5.2.3 Model III

Table 4. 13 Cut-off points, classification rates and type I and type II error rates for model III

Cut-off point	Classification rate (%)	Type I error rate (%)	Type II error rate (%)
0.1	79.10	31.03	0.00
0.2	83.70	20.69	7.14
0.3	83.70	20.69	7.14
0.4	81.40	17.24	21.43
0.5	86.00	10.34	21.43
0.6	83.70	10.34	28.57
0.7	81.40	6.90	42.86
0.8	76.70	3.45	64.29
0.9	72.10	0.00	85.71

Table 4.13 indicates the in-sample classification rates and type I and type II error rates for model III. It reveals that the in-sample classification rates for model III range from 72.10% to 86.00%. Type I error rates swing from 0% to 31.03%, while type II error rates stretch from 0% to 85.71%. The cut-off point of 0.5 is chosen as the optimal cut-off point since it is allied to the minimal sum of the two errors (31.77%) and a high model in-sample classification rate of 86.00%.

4.5.2.4 Model IV

Table 4.14 indicates the in-sample classification rates and type I and type II error rates for model IV.

Table 4. 14 Cut-off points, classification rates and type I and type II error rates for model IV

Cut-off point	Classification rate (%)	Type I error rate (%)	Type II error rate (%)
0.1	83.70	24.14	0.00
0.2	86.00	17.24	7.14
0.3	88.40	13.79	7.14
0.4	90.70	10.34	7.14
0.5	93.00	6.90	7.14
0.6	90.70	3.45	21.42
0.7	88.40	3.45	28.57
0.8	83.70	3.45	42.86
0.9	79.10	3.45	57.14

Table 4.14 shows that the in-sample classification rates for model IV stretch from 79.10% to 93.00%. Type I error rates span from 3.45% to 24.14%, while type II error rates range from 0% to 57.14%. The cut-off point of 0.5 is selected as the optimal cut-off point because it is linked with the minimal sum of the two errors (14.04%) and a high model in-sample classification rate of 93.00%. Fascinatingly, model III has an in-sample classification rate of 86.00%, while model IV has an in-sample classification rate of 93.00%, signifying that the incorporation of macroeconomic factors improves the forecasting ability of the default prediction models for unaudited Zimbabwean privately-owned firms.

4.6 Discussion

This section discusses the results of each created model. To evaluate the significance of the determinants of the probability of default for audited and unaudited Zimbabwean privately-traded corporations included in the designed four stepwise logit regression models, the Wald test is implemented. The Wald test is applied to examine whether a predictor variable is statistically significant or not. If the Wald test p-value of the predictor is below the 5% confidence level (typically $p \leq 0.05$), it shows that the predictor outstandingly contributes to the predictive ability of the designed logistic regression model. Contrariwise, if the Wald test p-value of the driver is above the 5% confidence level ($p > 0.05$), it indicates that the driver is statistically insignificant. The

drivers with $p > 0.05$ are removed from the models and those with $p \leq 0.05$ are incorporated into the models.

4.6.1 Model I

Table 4.15 presents variables, with their corresponding p-values based on the Wald test, incorporated into model I.

Table 4. 15 Model I results reflecting coefficient estimates

Variable	Coefficient	Wald	Significance
(CA-CL)/TA	-2.117	15.915	0.000
EBIT/TA	-1.922	12.882	0.000
AG	-0.342	7.001	0.008
NS/NSLY	-1.218	31.184	0.000
TwB	-0.578	31.114	0.000
EBIT/TL	0.652	17.805	0.000
CA/TA	0.875	18.207	0.000
BD/TA	1.973	24.647	0.000
SD/TA	1.579	22.314	0.000
AR/NS	0.453	23.913	0.000
Constant	-1.784	14.573	0.000

See Table 4.1 for ratio definitions.

It has emerged that there are no substantial correlations between the predictors included in model I (see Table 4.16). Hence, Model I is not influenced by multicollinearity.

Table 4. 16 Correlation coefficients between variables included in model I

	BD/TA	SD/TA	AR/NS	EBIT/TA	(CA-CL)/TA	EBIT/TL	CA/TA	NS/NSLY	AG	TwB
BD/TA	1									
SD/TA	0 346	1								
AR/NS	-0 057	-0 020	1							
EBIT/TA	-0 100	-0 053	-0 131	1						
(CA-CL)/TA	-0 173	-0 059	0 058	0 430	1					
EBIT/TL	-0 149	-0 156	-0 114	0 582	0 250	1				
CA/TA	-0 156	0 095	-0 214	0 077	0 414	-0 331	1			
NS/NSLY	-0 057	-0 129	-0 107	-0 097	-0 241	-0 163	0 013	1		
AG	-0 088	-0 226	0 180	-0 100	-0 043	-0 061	-0 264	-0 014	1	
TwB	-0 147	-0 050	-0 250	-0 172	-0 164	-0 185	0 256	-0 333	0 086	1

The empirical results indicate that all predictor variables included in model I are greatly linked to the default probability for audited Zimbabwean private corporations with the ratio of (current assets-current liabilities)/total assets, the ratio of earnings before interest and tax/total assets, the net sales/net sales last year ratio, the time with the bank and the age of the firm having a negative impact on the probability default, and the ratios of earnings before interest and tax/total liabilities, short-term debt/total assets, current assets/total assets, accounts receivable/net sales and bank debt/total assets having a positive impact on the probability of default.

Profitability has a substantial impact on the private firm default probability. The ratio of earnings before interest and tax/total assets enters model I with a negative sign, indicating that default probability falls as the ratio increases. This proposition is in agreement with that obtainable in the existent literature for publicly traded and privately-owned companies in both developed and developing economies (Bauer and Edresz, 2016; Charalambakis and Garrett, 2016; Charalambakis, 2015; Charalambakis, 2014; Hayden, 2011; Ohlson, 1980; Shumway, 2001). Charalambakis and Garrett (2019) found a negative correlation between the financial distress probability and profitability for Greek private firms. Using a massive sample of bank loans to private Danish firms, Jensen, Lando and Medhat (2017) confirmed that profitability is negatively associated with the probability of default. Likewise, Durica, Valaskova and Janoskova (2019) exposed a negative correlation between the three profitability ratios (return on equity, return on assets and profit margin) and the business failure of corporates in the economies of the Visegrad Group (V4). V4 is a political and cultural coalition of four Central European nations - Hungary, the Czech Republic, Slovakia and Poland. Further, Altman, Sabato and Wilson (2010) found a negative relationship between the financial distress probability and profitability for UK SMEs while Altman

and Sabato (2007) revealed a negative correlation between the probability of financial distress and profitability for US SMEs.

Experimental results reveal that the (current assets-current liabilities)/total assets ratio is associated with a negative sign as expected, suggesting that as the ratio rises, the probability of default increases. As a liquidity ratio, this ratio measures the degree to which a company has liquid assets comparative to total liabilities. Therefore, the more liquid the Zimbabwean private firms are, the lower their default probability. This supposition is in line with the findings of Altman, Sabato and Wilson (2010) and Altman and Sabato (2007) for UK and US SMEs, respectively. In the study by Jensen, Lando and Medhat (2017), the quick ratio as a measure of liquidity had a substantial negative relationship with the probability of default for private Danish corporates, endorsing the proposition that the more liquidity a corporate has, the higher its capacity to pay unanticipated cash deficits that would otherwise have caused a default. Durica, Valaskova and Janoskova (2019) also discovered a negative association between the (current assets-current liabilities)/total assets ratio and the failure of firms operating in V4 countries. Moreover, Charalambakis and Garrett (2019) and Charalambakis (2014) found a negative relationship between the probability of financial distress and liquidity for Greek privately-owned corporates and Bauer and Edresz (2016) predicted the bankruptcy probabilities for Hungarian firms and revealed a negative relationship between liquidity and the probability of bankruptcy.

The a priori expectation is that as the age of the company increases, the default probability falls. As reported by Succurro (2017), Kenney, Cava and Rodgers (2016), Succurro and Mannarino (2013) and Chava and Jarrow (2004), it is observed that the age of the firm enters model I with a negative sign, indicating that young and adolescent corporations are associated with higher default risk than mature and established firm. Mature and established Zimbabwean private firms have entrenched a status, a footing and a particular market power and they are associated with elevated levels of reliability and accountability due to their stability. On the other hand, youthful Zimbabwean private corporates mainly fail because they face many internal challenges, battle more with distressed economic and financial conditions and wrangle more with magnified levels of competition. Internal challenges include limited experience, unstable cash flows, incapability to adjust to environmental wishes and

poor managerial skills which makes difficult to fufill contractual obligations in time. Moreover, youthful Zimbabwean private corporations are overoptimistic about their judgments. Although they are undercapitalised, their overoptimistic decisions embolden them to exploit unworthy business prospects, thereby leading to high default rates. In support of this, Ucbasaran et al. (2010) indicated that start-ups and young firms are usually undercapitalised and they make unfit business decisions, which increases their chances of failure. Wang and Zhang (2018) also proffered that firm age and default risk are positively associated. However, some studies have found no projecting power for the age of the company in bankruptcy prediction (see, Situm, 2014 and Chancharat et al., 2010).

Pursuant to the existing studies (see Brindescu-Olariu, 2016; Bauer and Edresz, 2016; Charalambakis, 2015; Charalambakis, 2014; Hayden 2011), it has emerged that leverage measures, i.e., the bank debt/total assets and short-term debt/total assets ratios are associated with positive signs. This indicates that as these leverage ratios increase, probability of default rises. In agreement with this discovery, Jensen, Lando and Medhat (2017) confirmed that the leverage for Danish private firms and default probability are positively related. Altman, Sabato and Wilson (2010) and Altman and Sabato (2007) discovered a positive correlation between the probability of financial distress and leverage for UK and US SMEs, respectively. This finding is not surprising given that the majority of Zimbabwean privately-owned firms are often undercapitalised. Hence, they usually use debt to finance their working capital needs and growth. Since Zimbabwean private firms depend more on debt, they are hit hard under downturn conditions in which capital restraints are indispensable. The adoption of high leverage reduces private corporations' cover against adverse shocks. Falkenstein, Boral and Carty (2000) posited that the greater the leverage used by firms, the lower the cushion against antagonistic shocks. Further, the adoption of more debt by Zimbabwean private corporates under distressed economic and financial conditions results in their amplified default probabilities because income has to be used to pay back the debts even if earnings or cash flows go down. Also, credit comes at a cost which negatively affects corporate customers' ability to repay their debts (see, for instance, Aleksanyan and Huiban 2016). Given that several Zimbabwean private corporates are owned by the indigenous people with limited managerial skills and experience, they fail to meet their credit obligations under distressed economic and financial conditions.

The ex-ante expectation of the study concerning the sign of the regression coefficient for the time with the bank is vindicated, i.e., the time with the bank is associated with a negative sign, inferring that the lengthier a firm-bank relationship, the lower the firm's default probability. This suggests that loans of Zimbabwean private firms that have long-term lending associations with their banks before loan acquisition are linked with low probability of default. Zimbabwean private corporates with long-term associations with their banks are better able to survive downturn conditions than corporations with short-term associations with their banks. Long-lasting credit relationships offer stability to corporate obligors under distressed economic and financial conditions since obligors get assurance to get credit from banks under such circumstances and profit from low prices for services and reduced loan interest rates provided by the banks. Guarantees from banks to access credit increase the availability of financial resources when firms experience temporary shortfalls in revenues and are under illiquid conditions. Also, Zimbabwean private corporations with long-term associations with banks can renegotiate their credit conditions. Further, durable firm-bank credit relationships alleviate enticements, on the part of the obligors, to dissuade funds to non-core business activities, thereby reducing the probability of default. Using a large sample of bank loans to private Danish companies, Jensen, Lando and Medhat (2017) found a negative correlation between the length of the banking relationship and the default probability. Peltoniemi (2007) proposed that long-term firm-bank associations are valuable chiefly to high-risk firms, and Petersen (1999) claimed that a lending association between a firm obligor and bank generates value to the borrowing corporate in the form of, among other things, low interest rates and guarantee to get credit. Bodenhorn (2003) proffered that corporations with long-term firm-bank associations profit from fewer personal guarantees needed when acquiring loans, lower costs of credit and renegotiable loan conditions during a credit crunch. Bodenhorn (2003), Peltoniemi (2007) and Petersen (1999) have also observed that corporates with long-term firm-bank associations are linked with low default probability.

This study does not have a prior expectation of either a positive or negative sign for the regression coefficient for the net sales/net sales last year ratio that measures the stability of a corporate's performance. In the other words, the ratio of net sales/net sales last year is a measure of firm growth. The experiment discovers that the relationship between the ratio of net sales/net sales last year and the probability of default is

negative, suggesting that as the ratio increases, default probability falls. It is not a surprise for the ratio of net sales/net sales last year to have a negative coefficient since it is required, in reality, for a firm to expand instead of scaling down. In Zimbabwe it has become undisputable that private non-financial firms have to grow to be successful. Private firms need to expand in order to establish their existence and presence in the market and become self-sustainable. Basically, private firms that expand in size by increasing their sales can grow through external growth, internal enlargement and diversification into connected sectors. Further, greater sales may lead to greater profit, thereby reducing the probability of default associated with the firm. In support of this, Bauer and Edresz (2016) posited that sales growth is negatively associated with the probability of bankruptcy for Hungarian firms. However, this finding is not in agreement with Hayden (2011) who discovered a positive association between the probability of default for Austrian companies and the ratio of the net sales/net sales last year. Further, Bauer and Edresz (2016) averred that an increase in sales growth drops bankruptcy risk only up to a certain point.

Although the prior expectation is that the ratio of the earnings before interest and tax/total liabilities (which measures leverage) enters model I with a negative sign, the study reveals that this ratio is linked with a positive regression coefficient, indicating that as the probability of default increases, the ratio rises. This finding goes against intuition. However, this outcome is more motivated by the denominator (total liabilities) than the numerator (earnings before interest and tax). High levels of the ratio of earnings before interest and tax/total liabilities are the product of low levels of total liabilities as a result of low levels of trade credit. A number of Zimbabwean private corporations are of low creditworthiness and are entangled in debt. Thus, they cannot merely acquire formal credit from banks and other financial institutions. They depend more on suppliers' trade credit as an alternative to formal credit from financial organisations. Nevertheless, financially distressed corporates find it challenging to get suppliers' trade credit to uphold their sales. Even if they succeed in accessing suppliers' trade credit, its stream only ensues for a short spell before the suppliers become credit constrained and then reduce trade credit levels. Bastos and Pindado (2013) established the substitution hypothesis between suppliers' trade credit and bank credit under a financial crisis. The authors established that suppliers offset credit reduction from financial institutions when granting trade-credit to less creditworthy corporates. Bastos and Pindado (2013) further proposed that suppliers provide trade

credit for a short time before they become credit restricted and decrease their level of trade credit during financial crises. Generally, supplier firms in Zimbabwe have limited access to formal credit from financial institutions due to the prevailing liquidity crisis. This results in them having smaller cash holdings, which translates into condensed trade-credit levels to client firms. In agreement with this, Shenoy and Williams (2017) posited that supplier firms with more access to bank liquidity offer more trade credit to their clients, and supplier firms with limited access to bank liquidity offer limited trade credit to their clients. Given that no alternative credit sources are available to them, such restraints on suppliers' trade credit shove distressed corporates into default.

The study has an ex-ante expectation of the negative sign for the current assets/total assets ratio's coefficient. However, it is discovered that the ratio of current assets/total assets is linked with a positive sign, which is not congruent to that proposed in the literature (see, for example, Hayden 2011). The positive sign for the coefficient for the ratio of current assets/total assets goes against intuition. Nonetheless, this outcome is more motivated by the numerator (current assets) than the denominator (total assets). Several Zimbabwean private corporations use suppliers' trade credit as they cannot purchase goods and services on restricted terms such as cash on delivery (COD) and cannot easily access bank credit due to the extended liquidity squeeze in the economy. Reliance on trade credit and limited access to bank credit has a grave influence on the firms' ability to operate. A myriad of Zimbabwean private corporates is associated with high levels of accounts receivable (sine a Reliance on trade credit implies that), which they cannot gather timeously. If a trade debtor falls into default, losses witnessed by the trade creditor leads it into default. Using the same line of reasoning, Jacobson and Schedvin (2015) indicated that, owing to trade debtor failures, trade creditors witness substantial trade credit losses and their bankruptcy risks rise in the magnitude of assumed losses. Private corporates with high accounts receivable end up postponing or failing to meet their credit obligations, resulting in a credit contagion cascading effect. In the same vein, Bastos and Pindado (2013) suggested that a trade credit contagion frequently happens in the supply chain during a financial crisis. Further, Jorian and Zhang (2009) established that trade credit interfaces could transfer credit contagion in industrial corporations.

Consistent with the existing literature (see, for instance, Hayden, 2011), the study results reveal that the ratio of accounts receivable/net sales considerably and positively

affects the probability of default for Zimbabwean private firms, indicating that as the ratio rises, probability of default increases. The ratio of accounts receivable/net sales is an activity measure that indicates the degree to which a corporate has a significant proportion of assets in accounts that may be of particular value. Several Zimbabwean private firms are associated with higher accounts receivable. The customers' inability to buy goods on cash on delivery with restricted terms due to the liquidity calamity in the economy has led to high levels of accounts receivable in Zimbabwean privately-owned corporations. Further, credit restraints in the country cause corporates holding high-levels of accounts receivable to delay payments to their creditors, thereby creating default risk for private firms. Monteiro (2014) articulated that credit restrictions during a financial crisis cause companies holding high-levels of accounts receivable to defer payments to suppliers. Generally, high levels of accounts receivable adversely affect the profitability, liquidity and cash flow positions of private firms since they cannot be collected in time. Moreover, an increase in accounts receivable results in high contagion risk that stems from debtor default, leading to credit losses to the trade creditors. Those credit losses then shove the trade creditors into default and, successively, bankruptcy. Using the same line of reasoning, Bastos and Pindado (2013) articulated that a trade credit contagion regularly materialises in the supply chain in a financial crisis and Jorian and Zhang (2009) noted that trade credit relations can send credit contagion across industrial firms.

4.6.2 Model II

Table 4.17 outlines the variables, including their p-values based on the Wald test, included in model II.

Table 4. 17 Model II results reflecting coefficient estimates

Variable	Coefficient	Wald	Significance
(CA-CL)/TA	-2.168	12.957	0.000
EBIT/TA	-0.968	4.659	0.031
RGDP	-1.535	6.435	0.011
INF	-2.543	19.633	0.000
NS/NSLY	-0.578	31.114	0.000
TwB	-0.998	11.284	0.001
EBIT/TL	0.687	25.632	0.000
SD/TA	0.652	4.451	0.035
CA/TA	0.715	35.498	0.000
BD/TA	0.693	36.395	0.000
Constant	-4.849	6.902	0.009

See Table 4.1 for ratio definitions.

There are no considerable correlations between the predictors incorporated into Model II (see Table 4.18). Consequently, model II is not affected by multicollinearity.

Table 4. 18 Correlation coefficients between variables included in model II

	BD/TA	SD/TA	EBIT/TA	(CA-CL)/TA	EBIT/TL	CA/TA	NS/NSLY	TwB	RGDP	INF
BD/TA	1									
SD/TA	0 346	1								
EBIT/TA	-0 100	-0 053	1							
(CA-CL)/TA	-0 173	-0 059	0 430	1						
EBIT/TL	-0 149	-0 156	0 582	0 250	1					
CA/TA	-0 156	0 095	0 077	0 414	-0 331	1				
NS/NSLY	-0 057	-0 129	-0 097	-0 241	-0 163	0 013	1			
TwB	-0 147	-0 050	-0 172	-0 164	-0 185	0 256	-0 333	1		
RGDP	-0 315	0 273	0 144	0 137	-0 120	0 116	-0 139	0 259	1	
INF	-0 318	0 168	-0 030	0 049	-0 252	-0 044	-0 119	0 052	0 627	1

The experimental results show that all variables included in model II are substantially linked with the default probability for audited Zimbabwean privately-owned firms with the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the time with the bank, the real GDP growth rate, the inflation

rate and the net sales/net sales last year ratio having a negative effect on the probability of default, and the ratios of earnings before interest and tax/total liabilities, short-term debt/total assets, current assets/total assets and bank debt/total assets having a positive impact on the probability of default. It is observed that the signs for the estimated coefficients for the bank debt/total assets, short-term debt/total assets, earnings before interest and tax/total assets, earnings before interest and tax/total liabilities, current assets/total assets, net sales/net sales last year and (current assets-current liabilities)/total assets ratios and the time with the bank are similar to those in model I. After including the macroeconomic factors, the study finds that the real GDP growth rate and the inflation rate are statistically significant in predicting default probability for audited Zimbabwean private firms.

This study reveals that as real GDP rises, the probability of default decreases. Given that real GDP is an indicator of a nation's economic output modified for price variations, this finding is unsurprising. In the same vein, Charalambakis and Garrett (2019) posited that the real GDP growth rate and the probability of financial distress for Greek private corporations are negatively correlated. On the other hand, Jensen, Lando and Medhat (2017) revealed that the Danish real GDP growth is insignificant in predicting private firm default probability.

The inflation rate enters model II with a negative sign, which goes against intuition, indicating that as the inflation rate rises, the probability of default falls. However, this result can be justified. Inflation benefits borrowers by reducing the real value of loans, in that way making it easier for them to pay their loans. Further, the sample period under contemplation is associated with a deflation. Deflation results in condensed overall economic activity, a surge in unemployment rates, an increase in debt's real value and a decrease in investment (see, for example, Mahonde 2016). Masiyandima et al. (2018) argued that the advent of the American dollar as the main currency in Zimbabwe resulted in negative and low rates of inflation, which adversely affected the country's growth. Deflation also amplified the recession in Zimbabwe and led to a deflationary spiral. The rise in the real value of debts due to deflation made it challenging for Zimbabwean private corporates to repay outstanding credit facilities, resulting in high default frequencies. Conversely, Jensen, Lando and Medhat (2017) highlighted that inflation does not influence the Danish private firms' default probability.

4.6.3 Model III

Table 4.19 outlines the variables, including their p-values based on the Wald test, incorporated into model III.

Table 4. 19 Model III results reflecting coefficient estimates

Variable	Coefficient	Wald	Significance
(CA-CL)/TA	-1.926	8.405	0.004
EBIT/TA	-1.257	37.771	0.000
TwB	-0.302	31.178	0.000
(NS-MC)/PC	-1.219	36.306	0.000
AG	0.352	22.279	0.000
SD/TA	1.550	39.330	0.000
EBIT/TL	1.281	21.500	0.000
INT	0.347	16.097	0.000
NS/NSLY	0.737	18.127	0.000
CA/TA	1.293	17.237	0.000
Constant	-0.666	18.608	0.000

See Table 4.1 for ratio definitions.

It is noticed that there are no considerable correlations between the predictors incorporated into model III (see Table 4.20). Hence, model III is not affected by multicollinearity.

Table 4. 20 Correlation coefficients between variables included in model III

	SD/TA	(NS-MC)/PC	EBIT/TA	(CA-CL)/TA	EBIT/TL	CA/TA	NS/NSLY	INT	AGE	TwB
SD/TA	1									
(NS-MC)/PC	0 172	1								
EBIT/TA	-0 110	0 074	1							
(CA-CL)/TA	-0 077	0 008	-0 068	1						
EBIT/TL	-0 161	0 169	0 574	0 073	1					
CA/TA	0 113	0 034	-0 143	0 551	-0 274	1				
NS/NSLY	0 031	0 322	-0 034	-0 168	-0 171	-0 054	1			
INT	0 009	0 113	-0 115	-0 091	-0 137	0 208	0 352	1		
AGE	-0 112	-0 186	-0 056	0 020	-0 074	-0 007	0 207	0 089	1	
TwB	0 054	0 067	-0 107	-0 183	-0 205	0 198	0 252	0 345	0 241	1

The empirical results show that all variables included in model III are substantially related with the probability of default for unaudited Zimbabwean privately-owned corporations with the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the time with the bank and the (net sales-material costs)/personnel ratio having a negative effect on the probability of default, and the ratio of earnings before interest and tax/total liabilities, the short-term debt/total assets ratio, the interest rate, the age of the firm, the ratio of current assets/total assets and net sales/net sales last year ratio having a positive impact on the probability of default. It is detected that the signs for the estimated coefficients for the short-term debt/total assets, earnings before interest and tax/total assets, earnings before interest and tax/total liabilities, current assets/total assets and (current assets-current liabilities)/total assets ratios and the time with the bank are similar to those reported in models I and II.

As a measure of productivity, the ratio of (net sales-material costs)/personnel costs is associated with a negative coefficient, indicating that as the ratio increases, default probability falls. In the same vein, Hayden (2011) discovered that the higher the ratio of (net sales-material costs)/personnel costs, the lower the probability of default for Austrian firms, and the lower the (net sales-material costs)/personnel costs ratio, the higher the probability of default for Austrian companies. Aleksanyan and Huiban (2016) announced that company productivity is a crucial determinant of bankruptcy and revealed that productivity positively influences corporate default probability. Further, Jahur and Quadir (2012) argued that the major causes of corporate failure are weak accounting frameworks, substandard financial regulations and below-par productivity levels.

The empirical results reveal that as the age of the firm increases, the default probability increases, showing that older and mature private corporates are more exposed to default risk than young firms. Older and mature unaudited Zimbabwean private firms mainly fail due to lack of strategic foresight, increased competition, innovativeness inflexibility, economic slowdowns, costly organisational frameworks, high-cost pressures and lack of adaptability. This result is in agreement with the findings of Switzer, Wang and Zhang (2018), Kucher et al. (2018) and Aleksanyan and Huiban (2016). Kucher et al. (2018) highlighted that mature SMEs fight more with amplified competition and economic downturns. Further, Succurro and Mannarino (2013)

postulated that empirical studies in advanced countries found a negative correlation between bankruptcy and age, while research in developing countries discovered a positive relationship between bankruptcy and age.

This study finds compelling evidence indicating that the interest rate has a significant impact on the default probability for unaudited Zimbabwean private firms. There is a positive correlation between the interest rate and the default probability, suggesting that as the interest rate rises, default probability increases. Thus, it is concluded that high-interest rates are connected to high rates of default for unaudited Zimbabwean private corporates. High interest rates enlarge the debt load of firm obligors, making loans with high interest rates harder to repay and ultimately forcing the respective borrowers into default. This indicates that the interest rate has an intrinsic implicit cost on the loans granted by banks with inferences on loan defaults. In agreement with this finding, Everett and Watson (1998) proffered that the failure of small businesses is positively related with the interest rates. Michalkova, Adamko and Kovacova (2018) indicated that due to high interest rates, several firms can fail to repay their loans to the banks. Moreover, Gonzalez-Aguado and Suarez (2011) highlighted that, in the short-run, increases and decreases in interest rates escalate the firm’s default rate. However, Gonzalez-Aguado and Suarez (2011) further posited that, in the long run, high interest rates lead to lower firm default rates because high interest rates encourage lower target leverage across companies.

Growth factors act similar to a double-edged sword. Rapid decline and rapid growth increase the default probability of a firm. This study does not have a prior anticipation of either a positive or negative sign for the regression coefficient for the net sales/net sales last year ratio. In this study, it has emerged that the correlation between default probability for audited Zimbabwean privately-controlled corporations and the ratio of net sales/net sales last year is positive, indicating that as the ratio increases, default probability rises. In reality, it is desirable for a corporate to expand instead of scaling down. However, high sales growth is a significant source of high default risk, as indicated here. Zimbabwean private corporates have been experiencing growth phases due to an increase in demand for local goods and services as a result of the introduction of the 'Buy Zimbabwe' and 'Make Local Buy Local' campaigns by the government. These campaigns were launched to prevent colossal closures of local corporations due

to perennial viability problems. Given that the majority of the Zimbabwean private corporates are owned by the indigenous people with limited management abilities, the owners have found it challenging to cope with the management difficulties that come into existence due to rapid growth, resulting in high default frequencies. Moreover, the rapid sales growth has been financed through debts, which are challenging to service for several private corporates due to their continuous viability problems and vulnerability to idiosyncratic shocks. Using the same line of reasoning, Hayden (2011) found a positive relationship between default probability for Austrian firms and the ratio of the net sales/net sales last year. The author argued that, in most cases, firms that grow very rapidly might fail to solve the management difficulties that come into existence as a result of swift growth. Falkenstein, Boral and Carty (2000) also noticed that high growth of sales implies that a corporate is rapidly growing and that rapid growth is unlikely to be financed by generated profits, thus increasing debt and other associated risks such as bankruptcy.

4.6.4 Model IV

Variables incorporated in model IV are presented in Table 4.21.

Table 4. 21 Model IV results reflecting coefficient estimates

Variable	Coefficient	Wald	Significance
(CA-CL)/TA	-2.621	29.920	0.000
EBIT/TA	-1.750	16.502	0.000
TwB	-0.266	9.307	0.002
RGDP	-1.549	21.285	0.000
INF	-1.621	18.313	0.000
SD/TA	0.295	31.045	0.000
EBIT/TL	2.527	13.256	0.000
INT	0.389	24.042	0.000
NS/NSLY	0.604	22.603	0.000
CA/TA	1.775	25.362	0.000
Constant	-1.403	34.450	0.000

See Table 4.1 for ratio definitions.

This study reveals that there are no significant correlations between the predictors included in model IV (see Table 4.22). Thus, model IV is not influenced by multicollinearity.

Table 4. 22 Correlation coefficients between variables included in model IV

	SD/TA	EBIT/TA	(CA-CL)/TA	EBIT/TL	CA/TA	NS/NSLY	INT	TwB	RGDP	INF
SD/TA	1									
EBIT/TA	-0 110	1								
(CA-CL)/TA	-0 077	-0 068	1							
EBIT/TL	-0 161	0 574	0 073	1						
CA/TA	0 113	-0 143	0 551	-0 274	1					
NS/NSLY	0 031	-0 034	-0 168	-0 171	-0 054	1				
INT	0 009	-0 115	-0 091	-0 137	0 208	0 352	1			
TwB	0 054	-0 107	-0 183	-0 205	0 198	0 252	0 345	1		
RGDP	0 060	0 037	-0 125	0 341	-0 117	-0 172	-0 153	-0 092	1	
INF	0 062	0 229	0 118	0 326	0 072	-0 316	-0 213	-0 178	0 589	1

The empirical results show that all drivers of default probability incorporated into model IV are significantly related with the probability of default for unaudited Zimbabwean privately-owned firms with the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the time with the bank, the real GDP growth rate and the inflation rate having a negative effect on the probability of default, and the ratio of earnings before interest and tax/total liabilities, the short-term debt/total assets ratio, the interest rate, the ratio of net sales/net sales last year and the current assets/total assets ratio having a positive influence on the probability of default. It is perceived that the signs for the estimated coefficients for the short-term debt/total assets, earnings before interest and tax/total assets, earnings before interest and tax/total liabilities, current assets/total assets and (current assets-current liabilities)/total assets ratios and the time with the bank are similar to those in models I - III. The inflation rate and real GDP growth rate behave as in model II, while the interest rate and the net sales/net sales last year ratio act as in model III.

4.6.5 Comparison of variables incorporated into default models for audited and unaudited firms

The experimental results indicate that model II and IV best explain the default probability for audited and unaudited Zimbabwean private non-financial corporations, respectively. On one hand, the study discovers a negative effect of the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate, the inflation rate and the net sales/net sales last year ratio, and a positive effect of the bank debt/total assets,

earnings before interest and tax/total liabilities, short-term debt/total assets and current assets/total assets ratios on the default probability for audited Zimbabwean privately-owned corporations. On the other hand, the study discovered a negative effect of the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate and the inflation rate, and a positive effect of the earnings before interest and tax/total liabilities, short-term debt/total assets, net sales/net sales last year and current assets/total assets ratios and the interest rate on the default probability for unaudited Zimbabwean privately-owned corporations.

In both models (II and IV) the study finds a negative effect of the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate and the inflation rate, and a positive effect of the earnings before interest and tax/total liabilities, short-term debt/total assets and current assets/total assets ratios on the default probability for audited and unaudited Zimbabwean privately-owned corporates.

Further, in model II, the net sales/net sales last year ratio has a negative effect, and the bank debt/total assets ratio has a positive impact on the default probability for audited Zimbabwean privately-owned corporations. In model IV, both the interest rate and the net sales/net sales last year ratio have a positive effect on the default probability for unaudited Zimbabwean privately-owned firms. The net sales/net sales last year ratio enters model II with a negative sign but enters model IV with a positive sign. This could be explained by the fact that audited firms are not over ambitious so that they end up pursuing unworthy business prospects since auditors perform information and insurance roles. Auditing firms have the expertise and prowess to examine bankruptcy and advise firms on how to deal with it. On the other hand, unaudited corporations without the help of the auditors may be overoptimistic about their verdicts and their overoptimistic decisions may encourage them to pursue unworthy business prospects, in that way leading to high default rates.

The bank debt/total assets ratio enters model II with a positive sign but it is not included in model IV. The insignificance of the bank debt/total assets ratio in model IV could be explained by the fact that unaudited firms do not usually acquire significant

bank loans as compared to audited firms because banks are a little bit more reluctant to give them substantial loans since they pose higher default risk than audited counterparts. In support of this, of late, some banks have been demanding audited financial statements from the private firms before giving them loans. The interest rate enters model IV with a positive sign but it is no included in model II. This could be elucidated by the fact that creditors usually believe that audited firms have plausible earnings and are less risky. As a result, audited corporations benefit from low-interest rates on borrowed funds and low returns expected by investors. Basically, firms that present audited financial statements to creditors are characterised by lower costs of debt than corporates that do not since the cost of debt shows the probability of default related to the borrower.

4.7 Robustness checks

In this study, the omnibus tests, pseudo R^2 measures (i.e., Cox and Snell R^2 and Nagelkerke R^2) and Hosmer-Lemeshow tests are applied to examine the robustness of the developed models.

4.7.1 Omnibus tests of model coefficients

The omnibus tests results of the designed models are summarised in Table 4.23.

Table 4. 23 Omnibus tests of model coefficients

		Chi-square	df	Significance
Model I	Step	53.809	1	0.000
	Block	141.692	2	0.000
	Model	141.692	2	0.000
Model II	Step	61.094	1	0.000
	Block	202.786	3	0.000
	Model	202.786	3	0.000
Model III	Step	18.734	1	0.000
	Block	237.769	5	0.000
	Model	237.769	5	0.000
Model IV	Step	51.556	1	0.000
	Block	196.968	3	0.000
	Model	196.968	3	0.000

The omnibus test reveals how well the created logit model performs. If the omnibus test p-value of the model is less than the 5% level of significance, the model is statistically significant; otherwise it is considered as insignificant. It is observed that the omnibus test p-values for all the designed models are below the 5% level of significance, indicating that these models are well fitted to the data and the included drivers are statistically significant.

4.7.2 Pseudo R^2 measures

Table 4.24 outlines the values of the Cox and Snell R^2 and Nagelkerke R^2 for the created models.

Table 4. 24 Models summary

	-2 Log likelihood	Cox and Snell R^2	Nagelkerke R^2
Model I	11.940	0.369	0.659
Model II	49.846	0.482	0.862
Model III	182.897	0.480	0.670
Model IV	142.096	0.546	0.762

The values of the Cox and Snell R^2 and Nagelkerke R^2 indicate how much of the variance in the response variable is explained by the created model. Literally, the Nagelkerke R^2 measure indicates that model I describes 65.90% of the variance in the response variable, while the Cox and Snell R^2 measure shows that model I explains 36.90% of the dependent variable variance. Hence, the predictors included in model I describe between 36.90% and 65.90% of the variance in the response variable. Using the same line of thinking, model II explains between 48.20% and 86.20% of the variance in the dependent variable, while model III defines between 48.00% and 67.00% of the variance in the response variable. Finally, model IV describes between 54.60% and 76.20% of the variance in the dependent variable. The Cox and Snell R^2 and Nagelkerke R^2 values show that the designed logistic regression models are good models.

4.7.3 Hosmer-Lemeshow test

The Hosmer-Lemeshow test results for the developed models are presented in Table 4.25.

Table 4. 25 Hosmer-Lemeshow tests for the generated models

	Chi-square	df	Significance
Model I	12.080	7	0.098
Model II	1.283	7	0.989
Model III	10.110	8	0.257
Model IV	6.427	8	0.600

The Hosmer-Lemeshow test indicates how close the estimated values are to observed values. If the Hosmer-Lemeshow test p-value is more than 5%, the dependent variable's actual and estimated values are nearly similar; otherwise, they are not very similar. Consequently, the created model is well fitted to the data. The Hosmer-Lemeshow test p-values for the built logit models are greater than 5%, revealing that the designed models are well fitted to the data.

4.8 Conclusions

Of late, corporate default prediction has been attracting a lot of scientific and regulatory attention due to the occurrence of the recent 2007 – 2008 global economic and financial crisis, high social and economic costs of corporate failure and the rising demand for credit. The creation of credible corporate default forecasting models is an indispensable exercise in the discipline of corporate finance. Although a multiplicity of models has been developed to predict corporate probability of default, the forecasting of default probability for private firms in developing economies is a vital but an understudied zone in credit risk management. Consequently, this chapter proposed and analysed four stepwise logistic regression models to separately detect default probability audited and unaudited for Zimbabwean private firms under economic and financial stress twelve months in advance. The chapter's primary focus was on identifying and interpreting the coefficients of the selected predictor variables.

The research offers considerable evidence indicating that models including firm and loan characteristics, macroeconomic factors and accounting information best explain the default probability for audited and unaudited Zimbabwean private corporations. In

particular, the study found a negative effect of the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate, the inflation rate and the net sales/net sales last year ratio, and a positive effect of the bank debt/total assets, earnings before interest and tax/total liabilities, short-term debt/total assets and current assets/total assets ratios on the default probability for audited Zimbabwean privately-owned corporations. On the other hand, the study discovered a negative effect of the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate and the inflation rate, and a positive effect of the earnings before interest and tax/total liabilities, short-term debt/total assets, net sales/net sales last year and current assets/total assets ratios and the interest rate on the default probability for unaudited Zimbabwean privately-owned corporations.

This study's results show that accounting information is useful in differentiating between Zimbabwean private firms in default and those not in default in the context of distressed financial and economic conditions. Moreover, the study indicates that the inclusion of macroeconomic variables improves model fit and the prediction performance of default models. The study also reveals that the drivers of default risk for audited and unaudited Zimbabwean private firms are dissimilar. Thus, it is crucial to model bankruptcy risk for audited and unaudited private firms separately from a risk management perspective.

For future research, firstly, this study could be extended by employing more sophisticated models such as support vector machines, expert systems, artificial neural networks and machine learning. Secondly, to improve the generalisability of the results, massive data sets of audited and unaudited private firms could be adopted. Lastly, further studies could be conducted using more relevant drivers of private firm default probability to improve the models' prediction capacity.

From a credit risk standpoint and under the AIRB approach, it is crucial for banks to create risk models for the three key credit risk components, i.e., default probability, exposure at default and loss given default. Default probability, exposure at default and rate of recovery (or loss given default) and their associations are implemented in the determination of credit portfolios’ expected and unexpected losses. Chapters three and

four analysed the private firm default probability under downturn conditions in a developing economy. In the next chapter, chapter five, stepwise Ordinary Least Squares regression models are designed to forecast workout recovery rates for defaulted bank loans for private non-financial corporates in the context of distressed economic and financial conditions in a developing economy.

Chapter 5: Determinants of corporate loan recovery rates under economic and financial stress in a developing country

(This chapter is under review in Financial Innovation)

5.1 Introduction

Basel II/III Advanced Internal Rating-based (AIRB) approach permits financial organisations to implement their default probability, exposure at default and rate of recovery or equivalently, loss given default forecasts in the determination of capital requirements. Although substantial research focus has been directed towards default probability estimation, limited research focus has been dedicated to rate of recovery or its inverse, loss given default, prediction (Yao, Crook and Andreeva, 2014; Zhang and Thomas, 2012). Swelling research effort has been focused to precise recovery rate computation of late. This has been in the backdrop of a decline in recovery values, a lack of quality data on recoveries and defaults, limited relevant predictor variables, the emergence of Basel II/III principles, a rise in the volume of defaulting borrowers due to the recent 2007 - 2008 recession and variations in recovery methodologies among financial institutions that were concerns in modern-day credit risk management.

The recovery rate for the *i*th account, $recovery\ rate_i$, is computed as follows

$$Recovery\ rate_i = 1 - \ loss\ given\ default_i,$$

where, $loss\ given\ default_i$is the loss given default for the *i*th account. Recovery rate refers to a portion of exposure recovered throughout the workout process, and its working definition is given by

Recovery rate = amount recovered/amount outstanding at default.

Accurate estimation of recovery rates is imperative for a number of reasons. Credit risk management and pricing depend on the precise appraisal of recovery rates upon default. Recovery rate forecasts help in the designing of collection policies to be implemented for defaulted firms and formulation of credit terms (see Ingermann et al., 2016). Wang et al. (2018) highlighted that accurate estimation of recovery rates leads to more efficient use of capital. Further, recovery rate is an essential fragment of the computation of capital levels that can be used as cushion to shield against credit losses under downturn conditions. Default probability, exposure at default and rate of recovery and their associations are employed in the determination of credit portfolios' expected

and unexpected losses, thus affecting the value at risk (Ingermann et al., 2016). Using the same line of reasoning, Wang et al. (2018) observed that the failure to precisely predict recovery rates in the credit risk process could result in under- or over-provisioning for the forthcoming loan losses.

Moreover, appropriate recovery rate models lead to reduced capital requirements (Ingermann et al., 2016). Also, it has emerged that accurate prediction of recovery rates can produce a competitive advantage and reduce challenges emanating from unfavourable picking owing to small variances in loan spreads (see Ingermann et al., 2016 and Gurtler and Hibbeln, 2013). Regulators need financial organisations to display evidence of recovery rates modelling to warrant that regulatory capital requirements are upheld. However, in the Basel II/III AIRB approach, there is no methodological precision regarding the models required for estimating recovery rates. This issue causes variability in the recovery rate models adopted between banks.

The majority of research papers have proposed recovery rate models for developed economies (see Wang et al., 2018; Francois, 2019; Ingermann et al., 2018; Khieu, Mullineaux and Yi, 2012), especially for corporate bonds since data for publicly-traded bonds is broadly available (Mora, 2015; Jankowitsch, Nagler and Subrahmanyam, 2014; Yao, Crook and Andreeva, 2014). Although bank loan recovery rate literature has been multiplying of late (Ingermann et al., 2018), it is generally restricted and is even more constrained in undeveloped markets. Existent literature on bank loan recovery rates is substantially devoted to advanced economies (Ingermann et al., 2018; Khieu, Mullineaux and Yi, 2012). Further, Khieu, Mullineaux and Yi (2012) posited that the mainstream of the extant literature on loan recovery rates come from the research work of practitioners, while research articles in the academic literature focus principally on the recovery rates of bonds. This is attributed to the scarcity of recovery data for bank loans since they are regarded as private debt instruments.

Also, literature on private firm recovery rates is exceptionally limited and is significantly focused on developed markets (see, for instance, Franks, de Servigny and Davydenko, 2004). This current study strives to predict recovery rates for private non-financial firm defaulted bank loans in a developing economy, that is, Zimbabwe, under economic and financial stress. This experiment is partly motivated by Basel II that encourages financial institutions to assign loss given default to each credit facility. Forecasting recovery rate for defaulted private corporate bank loans in an undeveloped

market under economic and financial stress is imperative for several reasons. Also, bank loans are significantly different to securities such as bonds and other traded corporate debts (Wang et al., 2018; Acharya, Bharath, and Srinivasan, 2007; Cantor and Varma, 2005; Franks and Torous, 1994; Gilson, 1990; Gilson, John and Lang, 1990). Private corporations are dominant firms in undeveloped markets (Charalambakis and Garrett, 2019; Slefendorfas, 2016; Organisation for Economic Co-operation and Development, 2015; Charalambakis, 2014). Bank loans granted to private firms are of high importance in Zimbabwe since a significant portion of the total bank loans is given to such type of firms. Moreover, it is not an inconsequential matter to predict recovery rates since the empirical research work on recovery rates usually presents low model forecasting ability, and there is no industry accord on which model is best suitable for modelling recovery rates.

Diverse economies or jurisdictions are characterised by distinctive settings such as rules, creditors' rights, reorganisation practices and legal systems which affect recoveries and do not allow the reapplication of recovery rate and loss given default models designed in them in different atmospheres (see Mora, 2015; Shibut and Singer, 2015; Peter, 2011; Davydenko and Franks, 2008; Bris, Welch and Zhu, 2006; Querci, 2005). In support of this, Franks, de Servigny and Davydenko (2004) computed recovery rates of firms in default whose data was gathered from 10 banks from 3 different economies. The authors revealed that due to different country-specific regimes of bankruptcy, recovery rates are substantially dissimilar among the three economies, particularly the United Kingdom (UK), Germany and France. The authors stated that the average values for the loss given default for the UK, Germany and France are 25%, 39% and 47%, respectively. Franks, de Servigny and Davydenko (2004) discovered that results were responsive to the adopted sample data and workout process regulatory structure.

Literally, the economic and regulatory settings of developed and undeveloped markets are not similar. For instance, Waqas and Md-Rus (2018) suggested that advanced economies have clearly stated bankruptcy laws and procedures, while undeveloped markets are deficient of such bankruptcy laws and procedures. Therefore, how each market allocates recovery risk premiums and the approach in which financial distress is ultimately dealt with generate diverse configurations for recovery rates across various developed and undeveloped economies. Thus, implementing recovery rate models

designed for advanced economies in undeveloped countries does not usually give dependable results.

The recent 2007 – 2008 global financial and economic crisis has highlighted the recovery rates' multifaceted and stochastic nature in the event of default (Jankowitsch, Nagler and Subrahmanyam, 2014). Basically, recovery rates are driven by endogenous factors (for example, firm and account characteristics) and exogenous factors (for example, macroeconomic variables). Interestingly, the incorporation of macroeconomic factors reduces uncertainty in forecasting recovery rates since they capture the effects of distressed economic and financial conditions and follows Basel II recommendation to predict the "downturn loss given default" (Bellotti and Crook, 2012). Although distressed economic and financial conditions are associated with low recovery rates, it is not crystal clear which variables may describe recovery rates in a better way under downturn conditions. Betz, Kellner and Rosch (2018) declared that the values of loss given default are based on recovery rates generated throughout different economic situations in the process of resolution and hence, it is a difficult task to select appropriate macroeconomic factors.

This analysis provides answers to the main questions below:

(i) What are the critical predictor variables of recovery rates for defaulted private non-financial firm bank loans under downturn conditions in a developing country?

(ii) Does the incorporation of macroeconomic variables result in improved recovery rate models?

(iii) How well do the designed models perform in predicting recovery rates?

In this study, these questions are explored by suggesting stepwise Ordinary Least Squares (OLS) regression models founded on diverse combinations of firm characteristics, loan features and macroeconomic factors in order to predict workout recovery rates for defaulted private non-financial firm bank loans in the context of economic and financial stress in a developing economy 12 months in advance. The study's principal focus is on the identification and economic interpretation of the predicted coefficients for the drivers included in the designed models. To fit the models, the study adopts a unique cross-sectional real-life data set of defaulted private firm bank loans accessed from a major anonymised Zimbabwean commercial bank over the

sample period 2010 - 2018. Geographically, the data set is an accurate picture of the Zimbabwean market. The author believes that this research project is the first piece of research work to analyse recovery rates for Zimbabwean privately-owned firm's defaulted bank loans.

Zimbabwe provides an exciting and challenging example in examining recovery rates for defaulted private firm bank loans in developing countries under economic and financial stress. Zimbabwe has been experiencing severe and extended downturn conditions over the past two decades which have promoted deindustrialisation and informalisation of the economy. In 2009, the nation phased out the Zimbabwean dollar and embraced a number of currencies which included the British pound, Botswana pula, euro, South African rand and American dollar to stabilise the economy. Nevertheless, the American dollar materialised as the presentation and functional currency of corporations. The advent of the American dollar as the chief currency caused negative and low inflation rates, which adversely affected the nation's growth (Masiyandima et al., 2018). Masiyandima et al. (2018) indicated that the country observed 28 uninterrupted months of negative inflation from October 2014 - January 2017. During the period under review, that is, 2010 -2018, the real gross domestic product (GDP) growth rate has fallen from more than 10% per annum in the period 2010 - 2012 to an average of 2.5% from 2013 - 2018 (World Bank Group, 2020a). The distressed economic and financial conditions observed in Zimbabwe are hardly experienced in advanced or even in other undeveloped markets. Therefore, the results of this examination can be compared to, but must not be expected to be similar to the results of other research work in recovery modelling.

In Zimbabwe there is a clear legal structure in resolving corporate financial distress issues. Distressed corporations can be liquidated or placed under judicial management. The purpose of judicial management is to offer sustainable firms which are in financial difficulties a more even opportunity to rehabilitate themselves and be returned to profitability. When a firm displays financial difficulties by failing to meet obligations when they fall due, an application for judicial management can be made to the courts by a corporation itself or creditors or shareholders or certain officials. The courts have discretion on judicial management. Also, creditors or distressed firms themselves or judicial managers can apply to the courts for the liquidation of the distressed firms. After the borrower's default on payment, a liquidation proceeding can be initiated by filing a petition with the courts. The courts then evaluate the petition and, if the balance

sheet of the firm shows that it is insolvent, the courts will support liquidation. The liquidation of firms and their placement under judicial management are guided by the Insolvency Act.

The judicial procedures for dealing with corporate bankruptcy affect the estimation of recovery rates. For instance, insolvency reforms in Zimbabwe permit an insolvency representative or a debtor to get new financing upon insolvency proceedings instigation. Further, World Bank Group (2020b) indicated that the costs related to the liquidation proceeding in Zimbabwe amount to about 22% of the worth of the estate of the borrower. These costs include attorney fees, court or government agency fees, fees of accountants, insolvency representative fees, etc.

The experimental results show that the firm size, the earnings before interest and tax/total assets ratio, the exposure at default, the length of the workout process, the total debt/total assets ratio, the ratio of (current assets – current liabilities)/total assets, the inflation rate, the interest rate, the collateral value and the real GDP growth rate are all significant determinants of recovery rates for Zimbabwean private non-financial corporate bank loans. In particular, the research project discovers a negative effect on the recovery rates, of the exposure at default, the length of the workout process, the total debt/total assets ratio and the interest rate on the recovery rates, and also a positive impact of the firm size, the ratio of earnings before interest and tax/total assets, the (current assets – current liabilities)/total assets ratio, the collateral value, the inflation rate and the real GDP growth rate. The included financial ratios are vital since they denote some of the most imperative credit risk factors, particularly, size, profitability, leverage and liquidity. In this study, it is determined that accounting information is useful in examining recovery rates for defaulted bank loans for private corporations under downturn conditions in a developing economy. Moreover, the research project reveals that the prediction results of recovery rate models are augmented by including macroeconomic factors. This research result is in line with the discovery of Bellotti and Crook (2012), who posited that recovery rate prediction models' forecasting results are improved by including macroeconomic variables.

The remainder of the chapter is set out as below. Section 5.2 outlines the literature review. The methodology is outlined in section 5.3, and in section 5.4 the data and variables are described. In section 5.5, the empirical results and analysis are stated.

Lastly, section 5.6 articulates the conclusions and possible directions for future research.

5.2 Literature review

Over the years, direct research focus has been conducted to practically assess the dynamics and determinants of rates of recovery. Nevertheless, a review of existent literature indicated that it is not trivial to recognise drivers of recovery rates (Bastos, 2010). Several techniques have been implemented to examine recovery rates (Khieu, Mullineaux and Yi, 2012; Acharya, Bharath and Srinivasan, 2007; Altman et al., 2005; Dullmann and Trapp, 2004; Chava, Stefanescu and Turnbull, 2011; Gupton and Stein, 2002). These econometric methods offer insights into the potential predictor variables of recovery rates.

The bulk of existent research work on recovery rates is significantly devoted to bonds. On the other hand, the empirical literature concerning the rates of recovery for bank loans is limited owing to the scarcity of data for loan recoveries, since loans are regarded as private debt instruments (Frye, 2000). Mora (2015) stated that recovery rates diverge significantly across categories of debt instruments. It has emerged that bank loans and bonds are characterised by diverse characteristics that make their respective recovery rates different. In support of this, several authors such as Acharya, Bharath, and Srinivasan (2007), Emery (2007) and Emery and Ou (2004) observed that bank loans are associated more with superior recovery rates than bonds. Therefore, applying models designed for bonds to banks loans may not produce good results.

Recovery rates of loans are usually bounded to the closed interval [0, 1] and have a bimodal distribution (Wang et al., 2018; Dermine and Neto de Carvalho, 2006; Araten, Jacobs and Varshney, 2004; Schuermann, 2004). Bimodality refers to a situation when recovery rates of loans are close to 100% (i.e., balance fully recovered) or 0% (i.e., no recovery or bankruptcy). Rates of recovery modelling using parametric techniques has been a challenging exercise in academic literature and banking practice since recovery rates have unusual distributional characteristics. Consequently, several non-parametric models have been suggested to accommodate recovery rates' bimodality (see Bastos, 2010). In some cases, authors (see, for instance, Qi and Zhao, 2011) indicated that non-parametric models are superior to parametric methods in modelling nonlinear associations between rates of recovery and their covariates.

However, even with the sophistication of the models designed to deal with bimodality, studies by Li et al. (2016) and Qi and Zhao (2011) argued that these models do not necessarily provide better model fit than the simpler models, such as linear regressions, when applied to real loss given default data. Yao, Crook and Andreeva (2014), Bellotti and Crook (2012) and Qi and Zhao (2011) highlighted that linear regression models can be compared with other sophisticated statistical models in terms of forecasting accuracies even though there is a possibility of making predictions which are out of the range between 0 and 1. In support of this, Zhang and Thomas (2012) specified that linear regression techniques are superior to hazard models in some circumstances. For instance, the authors declared that linear regression models have higher Spearman rank and R-square coefficients than hazard models in recovery rate modelling. Bellotti and Crook (2012) proposed that OLS techniques that incorporate macroeconomic factors perform superlative in loss given default prediction at portfolio and account stages on independent hold-out data matrices when compared to a Tobit model, Beta distribution transformation, decision tree model, and fractional logit transformation. Evidence from Zhang and Thomas (2012) indicated that practitioners, regulators and academics do not need to apply the most complex parametric techniques to model recovery rates and loss given default. Additionally, in practice, regression type models are usually preferred because they are flexible when modelling recovery rates. Ability, priorities, and time restrictions are some of the reasons why financial institutions employ regression-type models in recovery rates modelling.

Extant literature has shown that recovery rates are affected by loan features, firm characteristics, macroeconomic factors, industry factors and recovery process variables (see, for instance, Gambetti, Gauthier and Vrins, 2019; Nazemi and Fabozzi, 2018; Nazemi, Heidenreich and Fabozzi, 2018; Wang et al., 2018; Altman and Kalotay, 2014; Jankowitsch, Nagler and Subrahmanyam, 2014; Davydenko and Franks, 2008; Acharya, Bharath and Srinivasan, 2007; Bris, Welch and Zhu, 2006; Altman et al., 2005). Although numerous studies approve that the economy and the rates of recovery are related, they do not reach an agreement on the fundamental macroeconomic determinants of recovery rates. Moreover, credit atmosphere dynamics influence recovery rates. In support of this, Das and Hanouna (2007), Altman et al. (2005), Hu and Perraudin (2002) and Jokivuolle and Peura (2000) propounded that the recovery rates and aggregate default are negatively correlated.

5.3 Methodology

Literature review has revealed that recovery rates are influenced by loan features, firm characteristics, macroeconomic factors, industry factors and recovery process variables (Gambetti, Gauthier and Vrins, 2019; Nazemi and Fabozzi, 2018; Nazemi, Heidenreich and Fabozzi, 2018; Wang et al., 2018). Interestingly, Bellotti and Crook (2012) indicated that the forecasting results of recovery rate prediction models are improved by incorporating macroeconomic variables. This study proposes stepwise OLS regression models based on diverse mixtures of firm characteristics, loan features and macroeconomic variables to forecast workout recovery rates for defaulted private non-financial firm bank loans under downturn conditions in a developing economy 12 months in advance.

OLS is one of the widely used and convenient algorithms in banking and finance. OLS regression analysis is easily performed in a number of common statistical software packages. Collischon and Eberl (2020) and Verbeek (2017) indicated that an OLS regression model presents the most comprehensible, natural and quick benchmark for other linear models and for more advanced techniques. Further, Verbeek (2017, pp. 1) presented the following advantages of linear regression:

- Linear regression is a robust approach for examining the associations among several variables by linking one variable to a set of variables. It can recognise the influence of one variable while regulating for other recognisable differences.
- Linear regression is a simple and appropriate technique to assess an empirical association between one variable and a set of other variables.
- Linear regression estimated by OLS is the “best linear predictor”. The estimated linear amalgamation of regressors offers the closest approximation to the actual outcome in a given sample.
- OLS works sensibly well even if the model is not specified perfectly.

Hence, OLS is extensively used in recovery rate modelling (see, for example, Bellotti and Crook, 2012; Zhang and Thomas, 2012). Basically, linear regression models can be compared with more advanced statistical models such as hazard models in terms of predictive accuracies and, in reality, they are typically preferred because they are flexible when modelling recovery rates. Henceforth, OLS models can precisely describe the behaviour of recovery rates and loss given default under distressed economic and

financial conditions. In this chapter, some of the advantages of the OLS regression in recovery rate modelling have already been indicated under the literature review section.

This section gives an overview of the OLS regression model adopted in this study to examine recovery rate drivers in the Zimbabwean private non-financial firm bank loan market. The recovery rate of an instrument *i* defined as $recovery\ rate_i$ is given by

$$Recovery\ rate_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni} + \mu_i,$$

where, β_0 denotes the intercept, $\beta_1, \beta_2, \ldots, \beta_n$ represent the regression coefficients, x_1, x_2, …, x_n are independent factors which denote company characteristics, loan features and macroeconomic factors, and μ_i is the error term. Macroeconomic variables and financial ratios are incorporated with a time lag of 12 months before default. A 12-month lag permits estimates to twelve months ahead.

To evaluate the forecasting capacity of the designed rate of recovery models, this study implements the mean absolute error, root mean squared error, Spearman's correlation coefficient and coefficient of determination.

5.4 Sample and data

This study adopts a unique cross-sectional real-life data set of defaulted private non-financial firm bank loans gathered from a credit portfolio of a major anonymous Zimbabwean commercial bank over the sample period 2010 - 2018. Account default refers to a situation where a borrower is not likely to settle its debt commitments or more than 90 days past due on any substantial debt commitment (Basel Committee on Banking Supervision, 2006). Loterman (2013) and Basel Committee on Banking Supervision (2006) indicated that the three major components of the workout process are recoveries (cash or non-cash, i.e., collaterals), costs (direct or indirect) arising from the collection of recoveries and the discount rate used on cash flows from the recovery processes in order to express them in terms of monetary values at the default date. The data matrix comprises yearly cash inflows recovered by the bank after the default of the loans. Cash inflows include payments made by customers and cash inflows realised from collateral. In practice, recovery rate computation needs to incorporate material administration costs, whether direct or indirect, involved in executing and managing the workout process after loan account default. However, these costs are not considered in

this research work since information about them for the data matrix adopted is not available. The study computes recovery rate for each loan by discounting cash flows collected during the workout process to the date of default. Nevertheless, there is no harmony in the existent literature on which discount rate to use. In this study, the original contractual loan rate of interest is applied as the rate of discount. Chalupka and Kopecsni (2008) posited that the contractual loan rate of interest indicates the borrower's risk and opportunity cost of losing future payments.

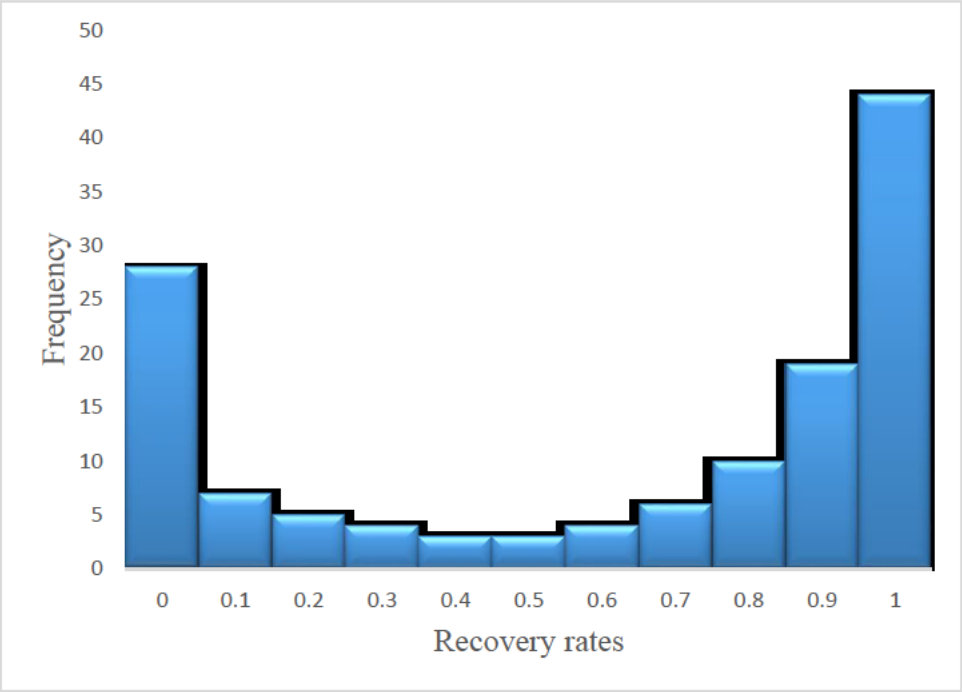
Non-defaulted private non-financial corporate bank loans are not considered in this study. Only defaulted loans are analysed since they are more thoroughly tracked and monitored than non-defaulted loans, resulting in current and accurate information about their current status. Further, banks receive additional explicit data (for instance, market data updates, verdicts gazetted throughout the workout process, etc.) and implicit data (for instance, time elapsed after default, etc.), which is not available before the borrowers' default.

The preliminary sample has a total of 136 defaulted privately-owned non-financial corporation bank loans. State-owned, multinational and financial organisations that do not show the typical Zimbabwean private firms' real features are excluded from the sample. Bank loans are observed and traced annually. Loan accounts with financial statements that cover time horizons less than 12 months or are recorded twice or more in the sample data or whose workout-processes have not been finalised are excluded from the sample. After data cleaning, 133 defaulted bank loans for 133 private non-financial firms remain in the final sample. The whole data set is employed to fit the OLS models, that is, the data set of interest is not segmented into training data set and validation data set owing to its relatively restricted size resulting from fewer observations. Segmenting the data set into training and testing data sets may introduce bias (see Xu and Goodacre, 2018). The data set meets the following conditions: (i) general mistakes are removed; (ii) default and payments data for all defaulted loans is available and reliable; and (iii) the quantity of observations is sufficient to guarantee statistically significant in-sample results.

Recovery rates must be between 0 and 1. To fit rates of recovery in the interval [0, 1], the distribution of rates of recovery is subjected to censoring. Some loans have negative recovery rates due to interests charged on them after default, while firm borrowers do

not pay anything. Hence, the outstanding balances keep on increasing. The recovery rates of these loans are pegged at 0. On the other hand, some loans have recovery rates that are more than 1. This happens when corporate borrowers settle the entire loan amounts at default plus interest and fees charged on them. The recovery rates for these loans are pegged at 1. Figure 5.I shows the recovery rate distribution after censoring.

Figure 5.1 Recovery rate distribution



From Figure 5.1, it is observed that the recovery rates are clustered close to 0% and 100% respectively. Conceptually, the estimated recovery rate is then subtracted from 100% to get the workout loss given default.

It is of special interest to indicate that the use of OLS models on censored recovery rate data may possibly bias the results, i.e., the regression coefficients may be biased (see, for instance, Amore and Murtinu, 2019). This is partly accredited to the fact that the censored recovery rate distribution violates one of the typical assumptions of OLS regression, i.e., there is a random sampling of observations, and the OLS regression models may not change the coefficients' estimates so that they may show the impact of censoring since censoring encompasses the removal of imperative regressors' variation. This may be regarded as a weakness of implementing OLS techniques on censored recovery rate data. However, OLS regression models are extensively implemented in examining censored recovery rate distributions in the existing literature (see, for

instance, Bellotti and Crook, 2012), which makes this thesis comparable to other studies.

In order to determine which drivers are related to the recovery rates for private non-financial corporate bank loans, the study concentrates on a set of determinants with firm characteristics, account features and macroeconomic variables (see Table 5.1). Considered in this analysis are recovery rate drivers that are common in the extant literature, appropriate to the experiment at hand and have the superior predictive ability in empirical and theoretical studies. The study examines the set of financial statements filed last, exactly a year before default in compiling accounting ratios. Macroeconomic factors are extracted from the World Bank Group, which is an online open-source. Table 5.1 also depicts the expected effects of candidate determinants on recovery rates. A positive (+) sign shows that an uptick in the value of the predictor results in a rise in the recovery rate while a negative (-) sign indicates a drop in the recovery rate given a rise in the predictor value.

Table 5. 1 Firm characteristics, account features and macroeconomic factors

Abbreviation	Variable	Expected effect	Source
Panel A: Firm characteristics			
AG	Firm age	+	Chalupka and Kopecsni (2008); Dermine and Neto de Carvalho (2006)
TwB	Time with the bank	-	Chalupka and Kopecsni (2008)
TA	Total assets (firm size)	+	Francois (2019)
NC	Number of creditors	-	Chalupka and Kopecsni (2008)
TD/TA	Total debt/total assets	-	-
(CA-CL)/TA	(Current assets-current liabilities)/total assets	+	Jacobs and Karagozoglu (2011)
EBIT/TA	Earnings before interest and tax/total assets	+	-
Panel B: Account features			
AAG	Age of account at default	+	Bellotti and Crook (2012)
EAD	Exposure at default	-	Bellotti and Crook

			(2012); Chalupka and Kopecsni (2008)
LN	Loan amount	-	Wang et al. (2018)
CLV	Collateral value	+	Ingermann et al. (2016); Gurtler and Hibbeln (2013)
LwP	Length of the workout process	-	Tanoue, Kawada and Yamashita, (2017); Betz, Kellner and Rosch, (2016)
LMP	Loan maturity period	-	Jankowitsch, Nagler and Subrahmanyam (2014); Jacobs and Karagozoglu (2011)
INT	Interest rate on loan	-	Nakayiza (2013)
Panel C: Macroeconomic factors			
GNIC	Gross national income per capita growth	+	-
RGDP	Real GDP growth rate	+	Park and Bang (2014)
INF	Inflation rate (% yearly average)	+	-
BB	Budget balance (% GDP)	-	-
PDE	Public debt (% GDP)	-	-
UR	Unemployment rate	-	Nazemi,

Heidenreich and Fabozzi (2018); Park and Bang (2014)

Firm age refers to the corporation's age from the day of its incorporation to the time of loan application. Time with the bank or length of business connection with the bank denotes the time the firm has been in a relationship with the bank. The number of creditors, representing capital structure features, refers to the quantity of creditors the corporation has borrowed from at the time of application. Accounting ratios included in this research project represent the significant risk factors in recovery rate analysis, that is, size of the corporate (book value of total assets), leverage (total debt/total assets ratio), liquidity ((current assets-current liabilities)/total assets ratio) and profitability (ratio of earnings before interest and tax/total assets).

The sample here consists of commercial bank (term) loans that disregard revolvers, bonds or mortgage loans. Exposure at default is the total exposure a financial entity faces on a debt facility when a borrower defaults. Loan amount refers to the initial loan amount advanced to the firm at the time of application, while the interest rate is the original interest rate for the contractual loan. The age of account at default refers to the age, in years, of the loan account from the opening date to the default date. Collateral value designates the value of collateral pledged by the private firm borrower when given a loan. The collateral forms include land, equipment, residential real estate and commercial real estate but disregard personal guarantees. The workout process length is the period between the points of default and the final loss claim or write-off of the asset. In other words, the period of recovery begins when a borrower defaults or workout or collections department takes on a client’s file and finishes when the file of the obligor is formally written-off or when the bank recuperates the amount owed and the debtor return to the active portfolio. Loan maturity period refers to the maturity period of the loan granted. Values of some account-specific characteristics are determined at the default time. Incorporating account information at default infers that the models are contingent on default.

It is widely documented that the rate of recovery and the default probability have a negative relationship (see, for example, Rosche and Scheule, 2011). Altman, Resti and Sironi, (2004) argued that the probability of default may not be considered as a predictor variable when designing recovery rate models because it is represented by the account-specific and firm-specific factors that are commonly applied when modelling probability of default and macroeconomic factors that can describe the common systematic risk to both recovery rate and probability of default. As a result, in this experiment, the default probability is not incorporated as an explanatory variable since it is represented by the account-specific and firm-specific characteristics that are normally used when estimating default probability and macroeconomic variables that can describe the common systematic risk to both default probability and recovery rate.

To lessen bias and escalate precision, missing values are imputed instead of eliminating observations with missing data. Mean imputation is implemented since it is quick, it is not computationally challenging and it sustains sample size (Song and Shepperd, 2007). In this technique, the average of non-missing values for each driver with missing value(s) is calculated. Each missing value is then replaced with the computed average. The firm's age and collateral value are each missing 0.75% of their values, translating into 1.5% of corporations with missing values. Outliers can substantially misrepresent the calculated model parameters and lead to incorrect inferences. To avoid the exclusion of the outliers from the sample data, extreme data points are winsorized at the distribution's 1^{st} and 99^{th} percentiles.

Table 5.2 outlines the descriptive statistics for firm features, account characteristics and macroeconomic variables for the entire sample.

Table 5. 2 Firm characteristics, account features and macroeconomic factors with descriptive statistics

Variable	Min	Max	Mean	SD
Panel A: Firm characteristics				
AG	2.00	85.00	25.72	23.33
TwB	1.00	21.00	6.45	4.63
TA*	3.13	212.37	33.95	54.29
NC	1.00	3.00	1.79	0.72
TD/TA	0.00	0.80	0.14	0.16
(CA-CL)/TA	-0.50	0.85	0.09	0.30
EBIT/TA	-0.51	0.36	0.04	0.14
Panel B: Account features				
AAG	1.00	4.00	1.43	0.63
EAD*	0.00	13.51	0.61	1.59
LS*	0.00	22.99	0.65	2.39
CLV*	0.00	19.03	1.87	3.71
LwP	1.00	7.00	2.82	1.46
LMP	1.00	6.00	2.47	1.15
INT	3.00	26.00	13.94	4.90
Panel C: Macroeconomic factors				
GNIC	-1.50	20.70	5.47	7.10
RGDP	0.70	19.70	5.60	6.63
INF	-2.40	10.60	0.93	2.98

BB	-11.20	-1.10	-4.10	3.86
PDE	37.10	54.20	43.76	6.37
UR	4.90	5.60	5.36	0.22

SD denotes standard deviation. *In millions of US dollars.

5.5 Empirical results and analysis

The study uses a stepwise selection technique with forward elimination to select the most statistically significant predictors at a 90% level of confidence. In stepwise selection, 0.15 and 0.20 are used as entry and removal probabilities, respectively, in order to include all relevant determinants of recovery rates (see, Hosmer and Lemeshow, 2000). Given two extremely correlated recovery rate determinants, one of them is excluded from the model(s) to deal with the multicollinearity problem since multicollinearity introduces bias in parameter estimates (Bade, Rosch and Scheule, 2011). Thus, developed OLS models are not influenced by multicollinearity (see Table 5.3).

Table 5. 3 Correlation coefficient matrix for recovery rate drivers incorporated into the models

	TD/TA	EBIT/TA	TA	(CA-CL)/TA	INT	AG	CTV	EAD	LWP	NC	LN	RGDP	INF
TD/TA	1												
EBIT/TA	-0 211	1											
TA	0 103	-0 109	1										
(CA-CL)/TA	-0 153	0 185	-0 157	1									
INT	0 128	-0 257	-0 194	0 141	1								
AG	0 000	-0 103	0 504	0 026	-0 188	1							
CTV	-0 062	-0 039	-0 133	0 127	0 101	-0 053	1						
EAD	0 086	-0 100	-0 023	0 015	0 089	0 079	0 152	1					
LWP	0 051	-0 070	0 085	-0 012	0 011	0 143	0 118	0 101	1				
NC	0 123	-0 098	0 111	-0 134	0 034	0 029	0 098	-0 085	0 094	1			
LN	0 129	-0 009	-0 006	-0 005	0 075	-0 009	0 111	0 787	-0 012	-0 106	1		
RGDP	-0 164	0 056	0 094	0 036	-0 166	0 121	0 044	0 190	-0 143	0 061	0 189	1	
INF	-0 088	-0 133	0 189	-0 027	-0 193	0 090	0 007	0 090	-0 066	-0 016	0 086	0 526	1

The study suggests two stepwise OLS regression models using diverse amalgamations of firm characteristics, account features and macroeconomic variables. Model 1 includes firm characteristics and account features, while model II incorporates firm characteristics, account features and macroeconomic variables.

5.5.1 Model I

Table 5. 4 Coefficient estimates for OLS rate of recovery model I

Variable	Coefficient estimate	SE	z	p > |z|
Constant	0.143	0.037	3.874	0.000
AG	0.146	0.036	4.064	0.000
TA	0.012	0.005	2.220	0.028
EBIT/TA	0.153	0.014	11.016	0.000
(CA-CL)/TA	0.169	0.037	4.595	0.000
TD/TA	-0.560	0.011	-5.305	0.000
LN	-0.138	0.020	-6.975	0.000
EAD	-0.025	0.006	-4.544	0.000
CLV	0.039	0.022	1.771	0.008
NC	-0.019	0.004	-4.813	0.000
LWP	-0.022	0.04	-5.458	0.000

SE denotes standard error. See Table 5.1 for ratio definitions.

The experimental results of this study indicate that all covariates included in model I are significantly connected to the recovery rate for defaulted Zimbabwean private non-financial firm bank loans, with the total debt/total assets ratio, the exposure at default, the loan amount, the number of creditors and the length of the workout process having a negative influence on the rate of recovery, and the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the age of the firm, the collateral value and the total assets having a positive influence on the rate of recovery.

It is observed that the firm age has a positive association with the recovery rates, reflecting that established and mature firms are associated with high recovery rates, while young and adolescent corporates are linked to low recovery rates. This is credited to the point that, compared to young and adolescent corporations, mature and established corporations have the experience, expertise and ability to effectively and

efficiently deal with the recovery processes, thereby increasing the recovery rates. In support of this finding, Chalupka and Kopecsni (2008) and Dermine and Neto de Carvalho (2006) posited that the firm's age positively influences the recovery rates. Conversely, Khieu, Mullineaux and Yi (2012) reported no association between recovery rates and age of firm.

As a proxy of corporate size, the total assets book value has a positive sign as expected, indicating that that big firms are associated with high recovery rates and small firms are characterised with low recovery rates. This proposition is in agreement with the research findings of Francois (2019) and Jacobs, Karagozoglu and Layish (2010). Wang et al. (2018) found that huge corporates are characterised by improved recovery rates during good times. Large defaulted Zimbabwean privately-owned non-financial firms are associated with high recovery rates due to the following reasons. They can efficiently and effectively steer a default and be transformed due to several aspects linked to size, such as market power and government support. Also, they offer less severe information asymmetry difficulties to banks. As a result, their reorganisation procedure happens more rapidly than that for smaller firms. On the other hand, small Zimbabwean corporations are more impacted by the domestic economy conditions than big firms and they lack the capability to service distressed loans, leading to low recovery rates. Contrastingly, Chalupka and Kopecsni (2008) proposed that if a huge firm defaults, several creditors compete for its assets, resulting in a low recovery rate for the bank. Wang et al. (2018) articulated that huge corporations may be associated with greater bankruptcy costs, leading to lesser recovery rates, especially under bad times. Moreover, Khieu, Mullineaux and Yi (2012) found no substantial association between recovery rates and firm size.

The loan amount enters model I with a negative sign as expected, indicating that recovery rates decrease as the loan amount increases. This shows that huge loans are associated with low recovery rates and small loans are linked to high recovery rates. Given that several recovery costs are semi-fixed, this finding is not surprising. Hence, the bigger the loan, the greater the recovery costs (making it difficult to repay huge loans) and the lower the recovery rates. This finding is supported by Dermine and De Carvalho (2006) and Felsovalyi and Hurt (1998). Wang et al. (2018) highlighted that the loan size is negatively related to the recovery rates whether the credit cycle is good or bad. Further, Dermine and De Carvalho (2006) posited that usually a bank defers

foreclosure on huge credit facilities since some bank customers who have business relations with a client with a huge loan in default would be negatively impacted by the foreclosure and could end up in default on their loans as well. The authors promulgated that this potential "spill-over effect" leads to lower rates of recovery when these huge credit facilities finally go in foreclosure. On the other hand, literature has indicated that financial institutions put more effort and resources into analysing borrowers' creditworthiness with huge loans and monitoring them, resulting in higher recovery rates. Acharya, Bharath, and Srinivasan (2007) noted that huge creditors' bargaining power may escalate recovery rates for enormous debts. Further, Khieu, Mullineaux and Yi (2012 and Thorburn (2000) reported that there is no relationship between rates of recovery and the size of the debt facility.

As expected, the collateral value has a significant positive sign, indicating that private firm borrowers with high-value collateral security are more easily recoverable than those with low-value collateral security. The economic import of this is that losses are less likely to happen if the collateral values are high since banks have a legitimate right to take hold of and sell particular assets pledged as security in case of default. Direct collateral realisation generates direct proceeds to the bank. Gurtler and Hibbeln (2013), Khieu, Mullineaux and Yi (2012), Qi and Yang (2009), Grunert and Weber (2009), Chalupka and Kopecsni (2008), Araten, Jacobs and Varshney (2004) and Van de Castle and Keisman (1999) supported the positive relationship between collateral value and rates of recovery.

The experimental outcomes reveal that the exposure at default enters model I with a negative coefficient as expected, indicating that the greater the exposure at default, the lower the rates of recovery. Fundamentally, the exposure at default indicates the proportion of the loan that is yet to be paid after default happens. Zimbabwean privately-owned firms have been facing perennial viability problems. Consequently, huge outstanding loan balances are more challenging for the Zimbabwean private firm obligors to pay back under economic and financial stress. If a significant part of the borrowed amount is not repaid before the occurrence of default, the recovery rate will be low and if a significant portion of the borrowed amount is reimbursed before the default, the rate of recovery will be great. This finding indicates that obligors with huge exposure at default expose the bank to more losses. Bellotti and Crook (2012), Bastos (2010), Chalupka and Kopecsni (2008) and Felsovalyi and Hurt (1998) supported this proposition. Nevertheless, this assertion is not consistent with the findings of Tanoue,

Kawada and Yamashita (2017) and Tong, Mues and Thomas (2013). Tanoue, Kawada and Yamashita (2017) suggested that the exposure at default positively influences the recovery probability, with a significant exposure at default resulting in a high recovery probability. A possible explanation for this is that banks strengthen their recovery efforts if the exposure at default is greater. Further, Tanoue, Kawada and Yamashita (2017) proposed that although a significant exposure at default results in a high recovery probability and makes the probability of incurring a loss low, obligors with huge exposure at default are likely to give rise to a loss.

This study confirms that the workout process's length has a substantial adverse influence on the rates of recovery, indicating that the recovery rates fall as the workout period escalates and the recovery rates rise as the workout period shortens. Generally, loan amounts increase with the workout period, especially for the longer time horizons, since the costs from expenses and forgone interest increase significantly as the workout period gets longer. Also, write-offs increase dramatically as the workout period increases. The distressed economic and financial conditions in Zimbabwe over the observation period have led to elongated and frail workout processes, resulting in low recovery rates. Several studies have confirmed that extended workout process results in low recovery rates (Tanoue, Kawada and Yamashita, 2017; Betz, Kellner and Rosch, 2016; Shibut and Singer, 2015; Gurtler and Hibbeln, 2013, 2011; Khieu, Mullineaux and Yi, 2012; Calabrese and Zenga, 2010; Caselli, Gatti and Querci, 2008). However, some authors (see, for instance, Ingermann et al., 2016; Querci, 2005) indicated that there is no relationship between the rate of recovery and the length of the workout process.

As a profitability measure, the ratio of earnings before interest and tax/total assets is positively related to the rates of recovery as expected. This positive sign for the ratio of earnings before interest and tax/total assets is not surprising since profitability metrics indicate the feasibility of the defaulted company's business visions. Profitable firms can conduct successful resolution processes and hence, they are associated with superior recoveries, and unprofitable corporations find it challenging to conduct success resolution processes, leading to low recoveries. Among other authors, Jacobs, Karagozoglu and Layish (2010) supported this argument. Conversely, Jankowitsch, Nagler and Subrahmanyam (2014) recognised an insignificant relationship between recovery rates and profitability.

The study has a prior expectation of a negative sign for the total debt/total assets ratio's regression coefficient, which is a leverage indicator. This experiment discovers an inverse relationship between the private firm loan recovery rates and the ratio of total debt/total assets, indicating that as the ratio increases, recovery rates fall. This finding is not unexpected since credit comes at a cost which influences adversely the capacity of firm borrowers to reimburse their loans. Since 2016, Zimbabwe has been experiencing chronic liquidity challenges. Thus, the usage of high levels of leverage by private firms has weakened their cover against liquidity shocks, leading to low rates of recovery. This result is in agreement with the research outcomes of Francois (2019), Khieu, Mullineaux and Yi (2012), Carey and Gordy (2007), Acharya, Bharath and Srinivasan (2007) and Cantor and Varma (2005). Acharya, Bharath and Srinivasan (2007) articulated that corporations with greater leverage levels are connected to a higher scattering of debt ownership, which makes it difficult to hold talks regarding restructuring and leads to low rates of recovery. However, some studies discovered a positive correlation between rates of recovery and leverage since firms with greater leverage levels are exposed to increased monitoring by banks, thereby increasing the recovery rates. Nonetheless, Wang et al. (2018) and Jankowitsch, Nagler and Subrahmanyam (2014) found that leverage is not substantially linked to recovery rates.

As a liquidity measure, the (current assets-current liabilities)/total assets ratio enters model I with a positive sign as expected, indicating that recovery rates increase as the ratio rises. That is to say, recovery rates are low when dealing with defaulted loans for illiquid private firms. High levels of liquidity allow private firms to meet their short-term obligations. Zimbabwe has been witnessing a severe liquidity squeeze in its currency system since 2016, resulting in low recovery rates as private firms fail to honour their obligations. In support of this, Francois (2019), Jankowitsch, Nagler and Subrahmanyam (2014) and Varma and Cantor (2005) discovered a positive relationship between rates of recovery and liquidity.

The amount of creditors, as a proxy for the private corporate capital structure, is negatively correlated with the recovery rates as expected, indicating that as the number of creditors increases, the recovery rates fall. Most Zimbabwean private corporations are often undercapitalised. Hence, they usually employ debt sourced from a number of creditors to finance their working capital needs and growth. Due to incessant viability challenges mainly caused by the existence of distressed financial and economic conditions, the majority of these private corporations have failed to pay-off their

outstanding debts pooled from a number of creditors, leading to low recovery rates. Moreover, a challenging resolution process characterises private firms with several creditors as creditors compete for the corporations' assets, resulting in low recovery rates. In agreement with this assertion, Chalupka and Kopecsni (2008) discovered that a borrower with several loans is associated with a low recovery rate.

5.5.2 Model II

Table 5. 5 Coefficient estimates for OLS rate of recovery model II

Variable	Coefficient estimate	SE	z	p > |z|
Constant	0.106	0.011	9.265	0.000
TA	0.011	0.005	2.186	0.032
CLV	0.016	0.005	3.044	0.003
EAD	-0.041	0.011	-3.718	0.000
(CA-CL)/TA	0.129	0.044	2.906	0.004
TD/TA	-0.174	0.028	-6.117	0.000
LWP	-0.026	0.012	-2.216	0.028
EBIT/TA	0.109	0.013	8.635	0.000
INT	-0.139	0.033	-3.597	0.000
INF	0.100	0.012	8.240	0.000
RGDP	0.115	0.011	10.155	0.000

SE denotes standard error. See Table 5.1 for ratio definitions.

The empirical findings reveal that all explanatory factors included in model II are considerably correlated with the recovery rate for defaulted Zimbabwean privately-owned non-financial firm bank loans, with the length of the workout process, the exposure at default, the total debt/total assets ratio and the interest rate having a negative influence on the rate of recovery, and the total assets, the collateral value, the (current assets-current liabilities)/total assets ratio, the ratio of earnings before interest and tax/total assets, the inflation rate and the real GDP growth rate, having a positive influence on the recovery rate. It is observed that the signs for the estimated coefficients

for the total debt/total assets ratio, the total assets, the exposure at default, the collateral value, the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio and the length of the workout process are similar to those in model I.

As expected, the interest rate enters model II with a negative sign. This indicates that the recovery rates decline as the interest rate rises and the recovery rates rise as the interest rate falls. Generally, higher interest rates make it more challenging for a firm borrower to repay its outstanding loan balances. Higher interest rates lower the recovery rates at the default time since the claim on the obligor continues to increase after default due to interest accruals. This proclamation is supported by the research results of Nakayiza (2013) and Kosak and Poljsak (2010). Using the same line of reasoning, Bellotti and Crook (2012) employed the UK retail banks' base interest rates and concluded that the interest rates at the default time and recovery rates are negatively related.

Model II's results confirm that macroeconomic variables influence the recovery rates as in the studies by Betz, Kellner and Rosch (2018), European Banking Authority (2017), Bellotti and Crook (2012), Jacobs and Karagozoglu (2011) and Schuermann (2004). However, Bijak and Thomas (2015), Calabrese (2014), Gurtler and Hibbeln (2013) and Bastos (2010) renounced macroeconomic factors in their experiments. Some authors (see Brumma, Urlichs and Schmidt, 2014; Acharya, Bharath and Srinivasan, 2007; Dermine and Neto de Carvalho, 2006) analysed the univariate significance of macroeconomic variables, which partially vanishes in a multivariate setting.

In particular, the real GDP growth rate enters model II with a positive sign as expected, indicating that as the real GDP growth rate increases, recovery rates rise. This discovered relationship is not surprising since a surge in the real GDP growth rate indicates that the economy is performing well. Further, existent literature revealed that recovery rates are lesser in times of recessions and greater during expansions (see, for instance, Hanson and Schuermann, 2004; Frye, 2000). Under stressed economic and financial conditions, debtors are less likely to reimburse their debts, which adversely impacts rates of recovery. Moreover, workout periods are lengthened during times of distress than during normal times (Shibut and Singer, 2015), resulting in low recovery rates. In the same vein, Park and Bang (2014), Han and Jang (2013) and Khieu, Mullineaux and Yi (2012) discovered a substantial relationship between the rate of

recovery and the real GDP growth. However, Wang et al. (2018) indicated that there is no association between the rates of recovery and the annual GDP growth, while Ingermann et al. (2016) observed that there is no significant association concerning rate of recovery and the real GDP growth.

The experimental results show that the rate of inflation and the rates of recovery are positively related, indicating that as the rate of inflation rises, recovery rates increase and as the inflation rate falls, recovery rates decrease. This is not surprising since inflation benefits borrowers by reducing the real value of loans, making it easier for them to pay their loans. Further, the observation period under review has been associated with a deflation which led to a decrease in economic activity, an upsurge in unemployment rates, a drop in investment, a rise in debt's real value and stifled economic growth and development (see, for example, Mahonde, 2016). Masiyandima et al. (2018) also argued that the emergence of the American dollar as the primary currency in Zimbabwe led to negative and low rates of inflation which impacted negatively on the country's growth. Deflation also exacerbated the recession in Zimbabwe and resulted in a deflationary spiral. Since Zimbabwean private firms use a lot of debt, an upsurge in the debts' real value due to deflation led to low recovery rates.

5.5.3 Performance metrics for recovery rate models

To analyse and discriminate the predictive capacity of the designed recovery rate models, the study uses the mean absolute error (MAE), root mean squared error (RMSE), Spearman's correlation Coefficient (α) and coefficient of determination (R^2) (see, Table 5.6). These performance metrics give the overall model fit indications based on the training sample. Each metric has its way of expressing the forecasting capability of the models in quantitative terms. These performance metrics measure either calibration or discrimination. Calibration shows how close to actual values are detected values, while discrimination implies the capacity to give a ranking of the response variable.

Table 5. 6 Summary of the performance metrics for recovery rate models

Metric	Measure	Worst	Best
RMSE	Calibration	$+\infty$	0
MAE	Calibration	$+\infty$	0
R^2	Discrimination	0	1
α	Discrimination	0	1

The RMSE refers to the residuals' standard deviation and it measures the accuracy of the estimates relative to the actual values. Mathematically, the RMSE is given by

$$\text{RMSE} = \sqrt{\frac{1}{l}\sum_{i=1}^{l}(f(x_i) - y_i)^2},$$

where x_i represents the sample *i* required value, y_i indicates the sample *i* estimated value and *l* is the sum of samples used.

The MAE refers to an average of the absolute errors. It is deduced by the forecasted and actual values' averaged absolute differences:

$$\text{MAE} = \frac{1}{l}\sum_{i=1}^{l}|f(x_i) - y_i|,$$

where, x_i denotes the sample *i* required value, y_i is the sample *i* estimated value and *l* represents the sum of samples adopted.

The Spearman's correlation coefficient ranks forecasted and actual values. It indicates how precise the ranking of the forecasted values is. The Spearman's correlation coefficient is given by

$$\alpha = 1 - \frac{6\sum_i^l d_i^2}{l(l^2-1)}$$

where, d_i represents the variance between the actual and estimated values' ranks. The Spearman's correlation coefficient takes the values between +1 (signifying perfect

positive relationship) and -1 (designating perfect negative relationship) with 0 showing no relationship.

The coefficient of determination is defined as the portion of described variance and is given by

$R^2 = 1 - \frac{SS_{err}}{SS_{tot}}$,

where, $SS_{tot} = \sum_{i=1}^{l}(y_i - \bar{y})^2$, $SS_{err} = \sum_{i=1}^{l}(y_i - f(x_i))^2$ and $\bar{y}$ denotes the average of the observed values.

The performance measures for rate of recovery models are outlined in Table 5.7.

Table 5. 7 Performance measures for rate of recovery models

Metric	**Model I**	**Model II**
RMSE	0.2555	0.2110
MAE	0.1410	0.1164
R^2	0.3348	0.4249
α	0.5227	0.6396

From Table 5.7, it is observed that model II outperforms model I in terms of all the performance metrics considered based on the training sample. Comparatively, the R^2 and α values for model II are greater than those for model I, while the MAE and RMSE estimates for model II are inferior to those for model I. For instance, the study discovers that model II is capable of explaining 42.49% of the variance in recovery rates while model I describes 33.48% of the variance in recovery rates. Therefore, this study concludes that incorporating macroeconomic variables into the recovery rate models gives a better model fit, resulting in substantial enhancement of the models' explanatory abilities. Although the model fit is weak across the developed models as indicated by R^2, such values are usual in recovery rate modelling. The results found in this experiment are comparable to the results discovered in other studies such as Ingermann

et al. (2016) and Zhang and Thomas (2012). For example, using the training sample, Zhang and Thomas (2012) created a recovery rate linear regression model and got an MSE of 0.1650, MAE of 0.3663, α of 0.3183 and R^2 of 0.1066.

5.6 Conclusions

In this chapter, stepwise OLS models founded on diverse combinations of firm characteristics, loan features and macroeconomic factors were suggested to predict recovery rates for defaulted private non-financial firm bank loans under financial and economic stress in a developing country (Zimbabwe). The principal research emphasis of this chapter was on the identification and economic interpretation of the predicted coefficients for the explanatory factors incorporated into the designed techniques. To fit the models, the study adopted unique data matrix of defaulted private non-financial firm bank loans accessed from an anonymous major Zimbabwean commercial bank over the observation period 2010 - 2018.

The experimental results indicated that the firm size, the collateral value, the exposure at default, the ratio of earnings before interest and tax/total assets, the length of the workout process, the total debt/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the inflation rate, the interest rate and the growth rate of the real GDP are all significant determinants of recovery rates for Zimbabwean private non-financial corporate bank loans. In this study, it is shown that accounting information is useful in examining recovery rates for private non-financial corporations under downturn conditions in an undeveloped market. Further, the research project reveals that the prediction results of recovery rate models are augmented by including macroeconomic factors.

For further research, this study may be improved in several dimensions. The study implements a restricted quantity of observations. This may introduce some bias in the estimation of recovery rates. Therefore, a vast sample data could be gathered and applied in the analysis of defaulted private non-financial firm bank loan recovery rates. By increasing the data set, further examinations on recovery rates' predictor variables for private firm defaulted bank loans under downturn conditions in developing countries can be done. Recovery rates systematically differ through time. Thus, dynamic models that consider time-varying changes systematically in the recovery rates can be

employed. Also, more appropriate predictor variables in a time variant framework can be combined to improve the models' prediction capacity. Although, in reality, it is a common practice to neglect the effect of censored recovery rate data on the coefficients of regressors, the nature of censored recovery rate distributions makes OLS regression models possibly unsuitable. Therefore, models for censored data could be implemented in modelling censored recovery rate data in order to improve the forecasting abilities of the models. Further, the study could be stretched to cover other financial instruments such as revolvers, mortgage loans and agricultural loans.

In addition to default probability (see chapters three and four) and rate of recovery (analysed in this current chapter, chapter five), the exposure at default is also an important parameter in the determination of credit portfolios' expected losses. Therefore, the next chapter, chapter six, designs ordinary least squares regression models to estimate the CCF in order to precisely predict, at the account level, the exposure at default for defaulted private non-financial corporations having credit lines under downturn conditions in a developing country.

Chapter 6: Determinants of corporate exposure at default under distressed economic and financial conditions in a developing economy: the case of Zimbabwe

(This chapter has been published in Risk Management (see Appendix A6.1))

6.1 Introduction

Basel II/III Advanced Internal Ratings-based approach allows financial institutions to determine their regulatory capital requirements using their computations of the probability of default, and exposure at default. In predictive modelling, probability of default techniques are well researched, while loss given default, and exposure at default methodologies are at their developmental stages (see, for instance, Gurtler, Hibbeln and Usselmann, 2018 and Jacobs Jr. and Bag, 2011). Research work in exposure at default modelling is hindered by several factors, which include lack of industry consensus on computation procedures and industry benchmarks, restricted empirical evidence, limited or unreliable or unavailability of internal and external data, unsuitability of external data, and scarce empirical estimation techniques (Luo and Murphy, 2020, Voloshyn, 2017, Bandyopadhyay, 2016, Leow and Crook, 2016, Basel Committee on Banking Supervision, 2016, Barakova and Parthasarathy, 2013, Bag and Jacobs Jr., 2012 and Jacobs Jr. and Bag, 2011).

In practice, it is vital to design dependable models that predict exposure at default as precisely as possible. Exposure at default estimates are imperative inputs into expected and unexpected loss prediction techniques, regulatory and economic capital models, impairment predicting, stress testing, pricing credit portfolios, and advising credit portfolio management (see Schutte et al., 2020, Luo and Murphy, 2020, Voloshyn, 2017, Bandyopadhyay, 2016, Leow and Crook, 2016, Tong et al., 2016, Zhao, Dwyer and Zhang, 2014 and Brown, 2011). Additionally, Bag and Jacobs Jr. (2012) and Brown (2011) posited that loss given default and exposure at default have a more significant impact on the minimal capital requirements than probability of default since they are linearly incorporated into capital requirement models. Thus, loss given default and exposure at default changes have critical influences on the financial institutions' capital and long-standing plans.

Financial Supervision Authority (UK) (2004, 2004a) proposed that exposure at default for on-balance sheet exposures refers to the unpaid amount, excluding any particular provisions. On the other hand, Brie and Belmajdoub (2020) and Brown (2011)

propounded that exposure at default for off-balance sheet exposures (e.g., revolving credit lines) is predicted as the current balance drawn plus the existing balance undrawn times the credit conversion factor (CCF) or loan equivalent exposure factor (LEQF). The CCF is the fraction of the current balance undrawn that will be withdrawn at the default time (Tong et al., 2016). Scandizzo (2016) articulated that the CCF refers to the predicted proportion of the undrawn amount drawn by the time of obligor default, if it ever occurs, in the context of economic downturn conditions within one year.

The revolving nature of credit lines poses several challenges when estimating exposure at default in reality. These challenges emanate from the possibility that the borrower can make additional withdrawals if the limit still permits (Bandyopadhyay, 2016). It is challenging for banks to estimate line stage outstanding balance if a line goes into default, particularly if it falls into default swiftly and withdraw significantly from the line just before default. This implies that the clients' current behaviour partly drives exposure at default for revolving debt facilities (Bandyopadhyay, 2016, Tong et al., 2016 and So et al., 2014). Luo and Murphy (2020) and Qi (2009) proposed that the behaviour of both obligors and lenders on the "race to default" conjointly determines exposure at default.

To predict exposure at default for revolving credit facilities, Basel II/III has proposed the implementation of historical data to examine the CCF (Valvonis, 2008). It is worth mentioning that although the CCFs are often referred to in Basel Accords, the Accords do not precisely require exposure at default models to apply the CCF computations. Brown (2011) proffered that the determination of the CCFs for off-balance sheet exposures is an imperative exercise because the current withdrawn balance is not a suitable indicator of the ultimate exposure at default because as the account approaches default, there is a possibility that additional money will be withdrawn from the account as long as the limit allows it. Thus, understanding the CCF's empirical behaviour is vital for financial institutions in their quest to design rational CCF assumptions. Interestingly, although there are regulatory requirements, there are no regulatory recommendations for designing the CCF and exposure at default models, exposing financial institutions to wide-ranging possibilities (Voloshyn, 2017, Scandizo, 2016 and Qi, 2009).

The modelling of exposure at default for private corporate credit lines under downturn conditions in developing countries is crucial due to several reasons. Of late, the use of lines of credit has generally been on the rise due to their expediency and financial

flexibility (see, for example, Zhao, Dwyer and Zhang, 2014, Jimenez, Lopez and Saurina, 2009, Chari, Christiano and Kehoe, 2008 and references therein). Bank credit lines are the mainspring of funding and liquidity for corporates and are an imperative business line and a significant spring of credit risk for banks (Pelzl and Valderrama, 2019, Voloshyn, 2017, Barakova and Parthasarathy, 2013, Jacobs Jr. and Bag, 2011 and Jimenez, Lopez and Saurina, 2009). The usage of credit line affects liquidity management, credit line pricing, capital prediction and expected losses estimation by financial institutions, and provides supplementary information about obligors' defaults and financial distress. Thus, credit lines denote a substantial contributor to the balance sheets of several banks. A great impetus in examining credit lines also emanates from their unique features compared to other credit instruments (see Bacham and Yang, 2019, Jacobs Jr. and Bag, 2011). Using the same line of reasoning, Luo and Murphy (2020) and Barakova and Pathasarathy (2013) indicated that the utilisation rates and exposure at default risk behaviour vary across products, respectively, e.g., revolving credit lines, construction loan-commitments, etc.

Private firms are the most common types of corporations in undeveloped markets (see Charalambakis and Garrett, 2019 and Slefendorfas, 2016), and they constitute the majority of corporates that ultimately fail. Credit lines to private firms are of high importance in developing economies since a significant portion of the credit lines is given to such type of corporates. Applying exposure at default models designed for off-balance sheet exposures of listed companies to off-balance sheet exposures of privately owned firms does not always give credible results since public, and private corporations are dissimilar. Compared to public firms, private corporations are smaller in size, use more leverage, depend more on bank loans and trade credit, invest more, and are characterised by greater borrowing costs (see, for instance, Asker, Farre-Mensa and Ljungqvist, 2012, Gao, Hartford and Li, 2012 and Michaely and Roberts, 2012). Moreover, publicly traded and privately-owned corporates are exposed to, among other factors, different regulatory and environmental variables. For instance, privately-held corporations are not obligated by law to reveal their comprehensive operating and financial information in most cases while publicly-traded corporates are subject to comprehensive disclosure laws about their financial conditions and operating information, among other things.

The majority of the existing corporate exposure at default literature is focused on publicly traded firms in developed economies (see Barakova and Pathasarathy, 2013,

Bag and Jacobs Jr., 2012, Jacobs Jr., 2010 and Jimenez, Lopez and Saurina, 2009) due to the availability of exposure at default data for listed corporations. In the regulatory and academic literature, only a few studies have analysed exposure at default for private corporations, of which the majority of them are focused on advanced markets (see, for instance, Zhao, Dwyer and Zhang, 2014, Barakova and Pathasarathy, 2013 and Agarwal, Chomsisengphet and Driscoll, 2004). The exposure at default literature for private corporations is even more limited in developing countries. Restricted exposure at default literature for privately traded corporates is mainly attributed to the lack of data for private corporations (Yang and Tkachenko, 2012), perhaps since financial institutions are not keen to share exposure at default data for scientific research work due to confidentiality reasons, especially if they are associated with a considerable track record of defaults.

Since developed and undeveloped countries are characterised by diverse financial and economic conditions and institutional features, implementing exposure at default models developed for advanced economies in undeveloped economies may not produce the desired results. Additionally, the association between exposure at default and its determinants changes as time periods, financial situations, and economic conditions change. Hence, the appropriateness and performance of the already existing exposure at default estimation techniques in the unique era is a practical interrogation that needs to be conducted due to the changes in time horizons, economic conditions, and financial situations.

It is widely documented that exposure at default estimates are sensitive to macroeconomic conditions (see Luo and Murphy, 2020). Since the outbreak of the 2007 - 2008 financial crisis, the estimation of corporate exposure at default under downturn conditions has received a lot of regulatory and scientific attention. Moral (2011) proposed that incorporating macroeconomic variables into exposure at default models increases the estimates' forward-looking character and the estimators' predictive capacity. An exposure at default model with macroeconomic factors closely trails present-day situations of the borrower, thereby generating precise estimates. However, there is no industry consensus on which macroeconomic factors are best appropriate for modelling exposure at default under distressed economic and financial conditions.

In this research project, ordinary least squares (OLS) regression models based on different amalgamations of borrower characteristics, account features, and

macroeconomic variables are designed to estimate the CCF in order to precisely predict the exposure at default, at the account level, for defaulted private non-financial corporations having credit lines under distressed economic and financial conditions in a developing economy. The primary focus this thesis is on identifying and interpreting the CCF determinants for the defaulted privately-owned corporates with credit lines. To fit the models, the study applies a unique real-life cross-sectional data set of defaulted credit lines for private corporations pooled from an anonymous major Zimbabwean commercial bank over the observation period 2010 to 2018 to fit the models.

From a conceptual standpoint, Zimbabwe is an ideal setting for investigating exposure at default for defaulted privately held corporations with credit lines in undeveloped markets in the context of economic and financial stress. Privately-owned corporations are the most common type of firms in Zimbabwe, and over the past two decades, Zimbabwe has been experiencing severe and stretched distressed economic and financial conditions. The government phased out the Zimbabwean dollar and assumed a basket of foreign currencies, encompassing American dollar, euro, South African rand, British pound, and Botswana pula to serene the economy in 2009. Nonetheless, the American dollar arose as the presentation and functional currency of corporates. However, the American dollar appearance as the principal currency triggered deflation, which harmfully impacted the economy's growth (Masiyandima et al., 2018). Masiyandima et al. (2018) further promulgated that Zimbabwe witnessed 28 successive months of negative inflation from October 2014 to January 2017. During the sample period, the real gross domestic product (GDP) growth rate has plummeted from an average of 16.9% per year in the epoch 2010 - 2012 to an average of 2.5% from 2013 - 2018 (World Bank Group, 2020a). Downturn conditions that have been witnessed in Zimbabwe are barely observed in both developed and undeveloped economies. Geographically, the data set is a true representation of the Zimbabwean market.

This study indicates that accounting information is essential in analysing the CCF for defaulted private corporations with credit lines under downturn conditions in a developing country. Also, the study gives evidence showing that a model that includes four account-specific, four firm-specific, and two macroeconomic variables is associated with the superior in-sample prediction performance as indicated by the coefficient of determination. In particular, the experiment finds a negative effect of the credit usage, the drawn amount, the total assets, the current ratio, the ratio of earnings before interest and tax/total assets, the real GDP growth rate, and the inflation rate, and

a positive effect of the committed amount, the time to default, and the ratio of bank debt/total assets on the CCF. The encompassed financial ratios are crucial because they represent some of the most significant credit risk factors, i.e., size, profitability, leverage, and liquidity. Further, the study reveals that the CCF models' forecasting results and the corresponding exposure at default estimates are augmented by including macroeconomic variables. This finding is in line with the postulation made by Moral (2011), who propounded that the exposure at default models' prediction results are enhanced by incorporating macroeconomic factors.

The remainder of the chapter is set out as below. Section 6.2 outlines the literature review. The methodology is presented in section 6.3 and section 6.4 describes the data and variables. In section 6.5, the experimental results are stated. Finally, section 6.6 articulates the conclusions and possible directions for future research.

6.2 Literature review

Regulatory documents such as Basel II and III do not prescribe any specific technique(s) for modelling exposure at default. In the empirical literature, several measures have been created that can be estimated on behalf of exposure at default (Baesens, Rosch and Scheule, 2016). Common measures estimated in lieu of exposure at default include the LEQF, Addition Utilisation Factor (AUF), Exposure at Default Factor (EADF), and CCF (see Luo and Murphy, 2020, Gurtler, Hibbeln, and Usselmann, 2018, Leow and Crook, 2016 and Hahn and Reitz, 2011). Jacobs Jr. (2010) estimated LEQF, CCF, and EADF using corporate revolving credit data and a generalised linear modelling framework. The authors compared the predictive accuracy properties of these measures. Using eight account level factors, Yang and Tkachenko (2012) predicted EADF and compared seven models using 500 commercial borrowers. Their study proposed several technical steps that can be used to improve exposure at default modelling.

The CCF distributions are bimodal, i.e., the CCF values are close to 0% (indicating no balance variation) or 100% (showing that the withdrawn amount has increased to the credit limit) and in-between, there is a relatively flat distribution (Voloshyn, 2017 and Tong et al., 2016). The bounded nature of the CCF distributions enables exposure at default to be equal to the credit limit when the CCF is equal to 1. However, in reality, it is usual to discover credit lines with exposure at default bigger than the credit limit due

to changes in credit limits, interest charges, etc. For this reason, several studies (see, for instance, Tong et al., 2016 and Taplin, Minh To and Hee, 2007) proposed models that directly forecast exposure at default and disregard the CCF formulation.

Nevertheless, Luo and Murphy (2020) proffered that predicting exposure at default dollar amounts directly is problematic since the distribution of exposure at default stretches from zero or very low to tremendously huge amounts. Tong et al. (2016) propounded that models that directly model exposure at default have limitations regarding drawn balances. The authors articulated that although Basel conformity needs the predicted exposure at default values to be at least equal to the credit line's withdrawn balance, direct exposure at default models may estimate exposure at default values that are less than the withdrawn balance. However, this consequence would not transpire for censored CCF models, where the CCF cannot assume values lower than zero (Tong et al., 2016). Moreover, Tong et al. (2016) promulgated that models estimating exposure at default directly are more complicated with more parameters to be forecasted; hence, for application in the industry, model designers should ponder possible implications of this level of difficulty for model auditing and application.

Although each one of the exposure at default conversion measures estimated in lieu of exposure at default has its own shortcomings (see Leow and Crook, 2016, Barakova and Pathasarathy, 2013, Yang and Tkachenko, 2012, Hahn and Reitz, 2011, Qi, 2009 and Jacobs Jr. 2010), Voloshyn (2017) propounded that the CCF is transparent, logical and easy to apply in reality. Yang and Tkachenko (2012) promulgated that the CCF techniques are more appropriate for exposure at default prediction because modelling exposure at default directly is a challenging task due to the rough scale of monetary balances and the CCF framework is less exposed to scaling problems since it is bounded to the closed interval [0, 1]. In the same vein, using a European bank retail portfolio, Gurtler, Hibbeln, and Usselmann (2018) forecasted expected loss from empirical estimates of CCF, LEQ, EADF, and exposure at default. The authors then concluded that the CCF is the most desirable.

The business cycle substantially influences the balance sheets, default probabilities, and credit line usage by companies. It has emerged that the credit line usage is associated with cyclical characteristics, i.e., credit line usage ratios rise during economic downturn conditions and fall during expansion periods (Bandyopadhyay, 2016, Zhao, Dwyer and Zhang, 2014 and Qi, 2009). This implies that, during downturn conditions when

obligors' credit quality is weakening, and aggregate default rates are considerably greater than average (Canals-Cerda, 2020), it is essential to assess revolving private firm exposures. Therefore, exposure at default models should reflect downturn conditions to prevent underestimating losses by financial institutions (see Leow and Crook, 2016).

Exposure at default is estimated as a function of several risk drivers. The determinants of exposure at default can be classified as account-specific, borrower-specific, lender-specific, industry-specific, and macroeconomic variables (see, for instance, Luo and Murphy, 2020, Zhao, Dwyer and Zhang, 2014, Barakova and Pathasarathy, 2013, Jacobs Jr., 2010, Jimenez, Lopez and Saurina, 2009 and Qi, 2009). Qi (2009) posited that models incorporating borrower attributes, account information variables, and macroeconomic factors as drivers of exposure at default provide superior predictive ability. Also, an exposure at default prediction approach that includes macroeconomic factors presents a framework suitable for stress testing under downturn conditions (Leow and Crook, 2016). However, in practice, it is not crystal clear which determinants are imperative in exposure at default modelling (see, for instance, Voloshyn, 2017 and Qi, 2009).

In reality, there is no consensus amongst researchers and practitioners over which approaches should be implemented for exposure at default modelling (Voloshyn, 2017). Nevertheless, Barakova and Pathasarathy (2013) suggested that modelling techniques chosen have a substantial impact on exposure at default estimates. As alternatives to exposure at default conversion measures, several techniques have been introduced in the literature to estimate exposure at default for revolving loans (see, for instance, Luo and Murphy, 2020, Osipenko, 2018, Osipenko and Crook, 2015 and Yang and Tkachenko, 2012). Of late, several studies (see Voloshyn, 2017, Tong et al., 2016, Zhao, Dwyer and Zhang, 2014, Yang and Tkachenko, 2012, Jacobs Jr., 2010 and Jimenez, Lopez and Saurina, 2009) have implemented novel dimensionless response variables such as the utilisation rate and the change in utilisation as opposed to exposure at default conversion measures. Using a credit card portfolio, Tong et al. (2016) suggested a mixture model with a zero-adjusted gamma distribution (which models exposure at default directly) and compared its performance to an OLS model (which also models exposure at default directly), three different CCF techniques (Tobit, OLS and fractional response regression models), a utilisation change model, a credit usage segmentation model and a survival exposure at default model. Leow and Crook (2016) introduced a mixture model in order to forecast personal credit card exposure at default. The authors

combined a discrete-time repeated events survival model and two panel modelling techniques involving drawn balance and credit limit models. As required by Basel II, Witzany (2011) suggested an advanced methodology for exposure at default estimation incorporating several approaches and the intensity of default modelling.

Nonetheless, even with the complexity of the techniques designed to deal with issues such as bimodality in exposure at default modelling, and to estimate exposure at default directly, studies by Tong et al. (2016) and Brown (2012, 2011) discovered that the predictive performance of these models is comparable to that of simpler models, such as linear regressions, when applied to real exposure at default data. Additionally, modelling approaches adopted in exposure at default prediction literature either use defaulted corporates (see, for instance, Jacobs Jr., 2010 and Araten and Jacobs Jr., 2001) or both defaulted and non-defaulted corporations (see Zhao, Dwyer and Zhang, 2014 and Jimenez, Lopez and Saurina, 2009). Interestingly, Zhao, Dwyer and Zhang (2014) proposed that the credit line usages of defaulted and non-defaulted corporations are described by two diverse sets of risk profiles.

6.3 Methodology

Exposure at default is predicted as a function of a number of risk drivers. These risk drivers can be categorised as account-specific, borrower-specific, lender-specific, industry-specific and macroeconomic factors (see, for example, Luo and Murphy, 2020; Zhao, Dwyer and Zhang, 2014; Barakova and Pathasarathy, 2013; Jacobs Jr., 2010; Jimenez, Lopez and Saurina, 2009; Qi, 2009). Qi (2009) argued that models which include borrower characteristics, account features and macroeconomic variables as drivers of exposure at default provide superior predictive ability. Further, Leow and Crook (2016) postulated that an exposure at default prediction approach that incorporates macroeconomic variables offers a framework suitable for stress testing under distressed economic and financial conditions.

To forecast exposure at default for credit facilities which revolve, Basel II/III has advocated for the usage of historical data to analyse the CCF (Valvonis, 2008). Nevertheless, although the CCFs are often discussed in Basel Accords, the Basel Accords do not specifically need exposure at default models to implement the CCF computations. Among a number of advantages of using the CCF framework in exposure at default prediction articulated in the introduction and literature review sections of this

chapter, Voloshyn (2017) postulated that the CCF is transparent and logical and is easy to implement in practice. Further, the CCF techniques are more fitting for exposure at default forecasting since modelling exposure at default directly is a problematic exercise due to the rough scale of monetary balances and the CCF structure is less exposed to scaling challenges since it is constrained to the closed interval [0, 1] (Yang and Tkachenko, 2012). In this current study, OLS regression models premised on different combinations of borrower features, account characteristics and macroeconomic variables are developed to predict the CCF in order to precisely estimate, at the account level, exposure at default for defaulted private non-financial corporates having credit lines under downturn conditions in a developing economy.

In corporate finance, OLS is one of the extensively implemented and convenient algorithms. OLS regression analysis is simply executed in several statistical software packages. An OLS regression model provides the most understandable, natural and fast yardstick for other linear techniques and for more advanced models (Collischon and Eberl, 2020; Verbeek, 2017). Moreover, Verbeek (2017, pp. 1) suggested the following linear regression advantages:

- For assessing the relationships between numerous factors by relating one factor to a set of factors, the linear regression is a robust approach. It can identify the impact of one factor while regulating for other identifiable differences.
- Linear regression is a simple and apposite approach to analyse an experimental relationship between one factor and a set of other factors.
- Linear regression forecasted by OLS is the "best linear predictor". The forecasted linear union of regressors provides the closest estimate to the actual result in a given sample.
- OLS operates reasonably well even if the technique is not specified perfectly.

Therefore, OLS models can accurately describe the behaviour of CCF under distressed economic and financial conditions since, in CCF modelling, the predictive ability of sophisticated models is comparable to that of OLS models. Some of the merits of using the OLS models in CCF modelling are articulated in the literature review section.

This section provides an overview of a standard OLS regression model (see Loterman, 2013; Brown, 2012), that is used to regress the CCF against its candidate determinants. From the forecasted CCFs, the loan account-level exposure at default values are then estimated.

Suppose x represents a scalar quantity, **x** is a column vector, $\mathbf{x}^T$ denotes a row vector set up employing the transpose T, **X** is a matrix, n represents the quantity of independent variables (i.e., borrower characteristics, account features, and macroeconomic variables we include with a time lag of twelve months) and *l* denotes the number of observations. The observation *i* is represented as $\mathbf{x}_i$, while variable *j* is shown as x_j. The response variable *y* (i.e., the CCF value) for observation *i* is denoted as y_i (or CCF_i). A regression technique fits a data set to a model y = f(**x**) + *e*, where y represents the response variable, **x** are the independent variables and *e* denotes the residual.

The OLS regression technique determines the optimal parameters $\mathbf{b}^T = [b_0, b_1, b_2, ..., b_n]$ to fit the linear model below to a particular data set:

$y = \mathbf{b}^T\mathbf{x}$,

where $\mathbf{x}^T = [1, x_1, x_2, ..., x_n]$. The OLS deals with this challenge by minimising the sum of the squared residuals:

$$\sum_{i=1}^{l}(e_i)^2 = \sum_{i=1}^{l}(y_i - \boldsymbol{b}^T\boldsymbol{x}_i)^2.$$

Deducing the derivative of this equation and consequently setting that derivative equal to zero:

$$\sum_{i=1}^{l}(y_i - \boldsymbol{b}^T\boldsymbol{X}_i)\,\boldsymbol{x}_i{}^T = 0,$$

the model parameters **b** can be recovered as:

$$\mathbf{b} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y},$$

with $\mathbf{X}^T = [\mathbf{x}_1, \mathbf{x}_2, \mathbf{...}, \mathbf{x}_n]$ and $\mathbf{y} = [y_1, y_2, ..., y_n]$.

We adopt a fixed-horizon approach in the computation of the CCF. Suppose $L(t_{d-12})_i$ denotes the credit limit 12 months prior to default for observation/account *i*, $E(t_{d-12})_i$ represents the drawn amount for account *i* at 12 months before default, t_d is the date of default and t_{d-12} is the reference date set at 12 months prior to default. The observed CCF_i for each account *i* with $L(t_{d-12}) \neq E(t_{d-12})$ is estimated using t_{d-12} as the reference date. For account *i*, the CCF_i is described by

$$CCF_i = \frac{E(t_d)_i - E(t_{d-12})_i}{L(t_{d-12})_i - E(t_{d-12})_i},$$

where $E(t_d)_i$ refers to the exposure for account i at the default time, $L(t_{d-12})_i$ is the credit limit 12 months before default for account i, $E(t_{d-12})_i$ denotes the drawn amount for account i at 12 months prior to default and t_{d-12} is set to 1 year.

From the forecasted CCF_i, a loan account-level exposure at default estimate, exposure at $default_i$, is deduced according to the model:

Exposure at $default_i$ = Present withdrawn $amount_i$ + CCF_i x Present undrawn $amount_i$.

6.4 Sample and data

In this study, a unique real-world cross-sectional data set of account level observations of defaulted credit lines for privately-traded non-financial firms pooled from an anonymous major Zimbabwean commercial bank over the observation period from 2010 to 2018 is emloyed. Account default refers to the condition when an obligor cannot fulfill its credit obligations according to the predefined terms or is more than 90 days past due on any substantial credit obligation (Basel Committee on Banking Supervision, 2006). The sample covers defaulted private corporations from different industries, and hence, it offers unique insights into the exposure at default risk features of diverse credit lines held by banks. Only defaulted credit lines are examined because they are traced and supervised thoroughly than non-defaulted credit lines, leading to the availability of up-to-date and precise information about their present status. Also, financial institutions get supplementary information that is not obtainable before the default of the obligors.

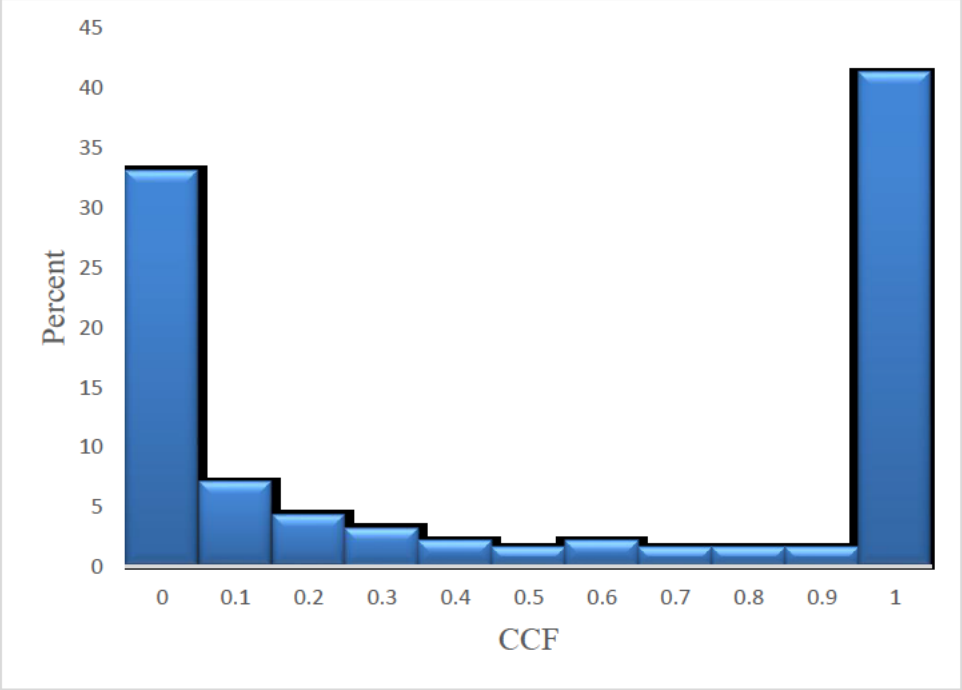
The initial sample has 188 defaulted lines of credit for privately-traded non-financial firms. In this study, credit lines for state-owned, multinational and financial institutions are dropped from the sample because they cannot show the typical Zimbabwean privately-owned corporates' actual characteristics. Accounts are observed and tracked yearly. Term loans, repeated observations, defaulted credit lines characterised by $L(t_{d-12}) < E(t_{d-12})$ and lines of credit with financial statements that cover time horizons less than 12 months before the date of default are omitted from the data set. After data cleaning, the final sample comprises 184 defaulted credit lines for 184 privately-traded corporations. This means that there is one observation per firm in the data set. In this experiment, the entire data matrix is applied to fit the OLS models. The data set is not divided into training and testing data sets because of its constrained size. Dividing this

thin data set into training and testing data sets would bring bias (see Yun and Royston 2018).

General mistakes are removed from the data, default data specific to each defaulted credit line is available and reliable and the observations' quantity is sufficient to guarantee statistically significant in-sample results. Therefore, the data set permits proper evaluation of exposure at default across privately-owned firms. Geographically, the data set is a factual representation of the Zimbabwean market.

Given that some CFFs are negative, and some are greater than one, the CCF distribution is censored to fit the CCFs into the interval [0, 1]. The CCF estimates greater than 100% are capped at 100%, and those less than 0% are floored at 0% as in Brown (2012), Jacobs Jr. (2010) and Qi (2009). The CCF limited between 0 and 1 is used in this analysis. In support of this, Brown (2012) propounded that it is challenging to estimate the unwinsorized CCF than the CCF winsorized between 0 and 1. The author also discovered that the unwinsorized CCF model has a weaker forecasting performance than the winsorized CCF model even if their results are implemented to predict the actual exposure at default. Figure 6.1 reports the empirical CCF distribution after censoring.

Figure 6.1 Distribution of CCF after censoring



The mean CCF value is 0.508, and the standard deviation is 0.457. This censored CCF's mean value is comparable to the mean CCF values reported in other studies such as Tong et al. (2016) and Jacobs Jr. (2010). Captivatingly, the CCF distribution reported in Figure 6.1 is bimodal, indicating similarities to the recovery rate and loss given default distributions reported in the extant literature (see, for instance, Wang et al., 2018, Ingermann et al., 2016, Bellotti and Crook, 2012 and Loterman et al., 2012).

It is of interest to mention that the use of OLS models on censored CCF data may potentially bias the results, i.e., the regression coefficients may be biased (see, for instance, Amore and Murtinu, 2019). This is partly attributed to the fact that the censored CCF distribution violates one of the classical assumptions of OLS regression, i.e., there is a random sampling of observations and the OLS regression models may not change the coefficients' forecasts so that they may reflect the impact of censoring since censoring encompasses the removal of imperative regressors' variation. This may be regarded as a weakness of implementing OLS techniques on censored CCF data. However, OLS regression models are widely used in analysing censored CCF distributions in extant literature (see, for example, Tong et al., 2016 and Brown, 2012), which makes this study comparable to other studies. Further, Brown (2012) directly forecasted the unwinsorised CCF using an OLS regression model and confirmed that it is more challenging to estimate the unwinsorised CCF than the CCF winsorised between 0 and 1. The author also discovered that the unwinsorised CCF model has a weaker forecasting performance than the winsorised CCF model even if their results are implemented to predict the actual exposure at default.

To determine which determinants are associated with the CCFs for defaulted credit lines for privately-held corporations, the study focuses on a set of candidate predictors with firm characteristics, account features, and macroeconomic variables (see Table 6.1). In this study, variables popular in the extant literature, relevant to the experiment and have superior predictive power in empirical research are adopted, the intention being to improve the developed models' predictive capacity. Previous research work is extended by considering new and potentially significant CCF drivers. To design the CCF models, the study uses account-specific, firm-specific and macroeconomic information gathered one year before default. In assembling the financial ratios, the last set of financial statements filed a year prior to default is analysed. Macroeconomic factors are pooled from an online open-source, the World Bank Group. Table 6.1 also shows the anticipated effects of potential drivers on CCFs. A positive (+) sign illustrates that an

increase in the determinant value results in a rise in the CCF value, while a negative (-) sign shows a fall in the CCF value given an uptick in the driver's value.

Table 6. 1 Account features, firm characteristics, and macroeconomic factors

Abbreviation	Variable	Notation	Expected effect
Panel A: Account features			
CA	Committed amount	$L(t_{d-12})$	+
DA	Drawn amount	$E(t_{d-12})$	-
UA	Undrawn amount	$L(t_{d-12}) - E(t_{d-12})$	+
DP	Drawn percentage	$E(t_{d-12})/ L(t_{d-12})$	-
UP	Undrawn percentage	$(L(t_{d-12})- E(t_{d-12}))/ L(t_{d-12})$	+
TTD	Time to default		+
CLV	Collateral value		-
LMP	Line maturity period		+
LAG	Line age		-
Panel B: Firm characteristics			
TA	Total assets (firm size)		-
TwB	Time with the bank		-
NB	Number of banking relationships		+
TD/TA	Total debt/total assets		+
BD/TA	Bank debt/total assets		+
AG	Age of the firm		-
EBIT/TA	Earnings before interest and tax/totals assets		-
CA/CL	Current assets/current liabilities ratio		-
Panel C: Macroeconomic factors			
GNIC	Gross national income per capita growth		-
RGDP	Real GDP growth rate		-

INF	Inflation rate (% yearly average)	+
BB	Budget balance (% GDP)	+
PDE	Public debt (% GDP)	+
UR	Unemployment rate	+

In this study, the committed amount, the drawn amount, the undrawn amount, the drawn percentage, the undrawn percentage, the time to default, the collateral value, the line maturity period, and the line age are introduced as the account-specific potential determinants of the CCF.

The drawn amount is the exposure, that is, the total amount outstanding on the credit line. Jacobs Jr. (2010) discovered that the drawn amount is inversely associated with the CCF. Thus, we anticipate a negative relationship between the drawn amount and the CCF. The amount committed is the recommended credit limit and the drawn percentage, also known as the utilisation rate or credit usage, refers to the exposure divided by the credit limit. Brown (2012) and Jacobs Jr. (2010) incorporated the committed amount and the credit usage as the determinants of the CCF in their experiments. They revealed that the committed amount is positively related to the CCF and the credit usage is adversely associated with the CCF. Therefore, in this research project, a positive association between the CCF and the committed amount, and a negative correlation between the credit usage and the CCF are expected.

Brown (2012) and Jacobs Jr. (2010) revealed that the undrawn amount, defined as the credit limit less exposure on the credit line, has a positive relationship with the CCF. Consequently, a positive correlation between the undrawn amount and the CCF is expected. The undrawn percentage is the undrawn amount divided by the credit limit. Tong et al. (2016) incorporated the undrawn percentage as a predictor variable in their study and found that it has a positive relationship with the exposure at default. Accordingly, this study expects that greater undrawn percentages are characterised by greater values of the CCF. The time to default denotes the time from the account opening date to default date. Jacobs Jr. (2010) observed that the time to default and the CCF are positively correlated. Hence, a positive relationship between the CCF and the time to default is expected.

The collateral value represents the monetary value of the collateral pledged by the corporation when granted the credit line. Jimenez, Lopez and Saurina (2009) postulated that collateralised credit lines are related to marginally lower rates of usage than uncollateralised lines, resulting in low exposure at default values for collateralised credit lines. Also, Zhao, Dwyer and Zhang (2014) suggested that if a corporation has collateralised and uncollateralised credit lines, it has inducements to withdraw more on the uncollateralised credit lines. Henceforth, an inverse association between the collateral value and the CCF is anticipated in this study. The line maturity denotes the credit line time to maturity in years. Jimenez, Lopez and Saurina (2009) indicated that credit lines with elongated maturity periods are associated with higher usage rates than one-year lines of credit. Thus, a positive association between the time to maturity of a credit line and the CCF is anticipated. The line age represents the number of years since the account was opened. Jimenez, Lopez and Saurina (2009) discovered that line age negatively relates to the usage rate. So, this research project anticipates a negative correlation between the line age and the CCF.

In this study, the total assets, the time with the bank, the number of banking relationships, the total debt/total assets ratio, the ratio of bank debt/total assets, the age of the firm, the current assets/current liabilities ratio and the ratio of earnings before interest and tax/total assets are introduced as the firm-specific candidate drivers of the CCF. It is widely documented in the extant literature that a corporation's financial condition affects its exposure at default estimates. Therefore, among corporate-specific variables, the study includes financial ratios. The financial ratios included in this analysis denote some of the critical risk factors in exposure at default examination, namely, total assets (size of the firm), leverage (the total debt/total assets and bank debt/total assets ratios), liquidity (the current assets/current liabilities ratio) and profitability (the ratio of earnings before interest and tax/total assets).

The time with the bank refers to the span of the relationship of the firm borrower with the bank underwriting the line of credit. Jimenez, Lopez and Saurina (2009) showed that the span of the banking relationship has a negative association with the usage of credit line, signifying that corporations with long-term firm-bank relationships do not withdraw as much as corporations with short-term firm-bank relationships. Hence, this study anticipates an inverse association between the CCF and the time with the bank. The number of the banking relationships represents the quantity of the banking relationships a firm borrower has. Jimenez, Lopez and Saurina (2009) indicated that the

amount of the banking relationships is positively associated with the credit line usage. So, a positive correlation between the CCF and the quantity of banking relationships is expected. The age of the firm refers to the age of the corporate borrower in years. Jimenez, Lopez and Saurina (2009) revealed a negative association between the credit line usage ratio and age of the corporate. Consequently, in this study an inverse association between the corporation's age and the CCF is expected.

In this research project, the corporate's size is represented by the total assets book value. Zhao, Dwyer and Zhang (2014) and Jimenez, Lopez and Saurina (2009) discovered that huge corporations are associated with low credit line utilisation. Thus, this study hopes for an inverse association between the corporate size and the CCF. The total debt/total assets ratio is a leverage measure given by the total debt divided by the book value of total assets. Another leverage measure, the bank debt/total assets ratio, is given by the bank debt divided by the total assets book value. Jacobs Jr. (2010) revealed a positive correlation between the bank debt/total assets ratio and the CCF and between the total debt/equity ratio and the CCF. Therefore, the study expects a positive association between the bank debt/total assets and the CCF and between the ratio of total debt/total assets and the CCF.

The current assets/current liabilities ratio measures liquidity. Jacobs Jr. (2010) revealed that liquidity, as measured by the current assets/current liabilities ratio, has an inverse correlation with the CCF. Accordingly, an inverse association between the CCF and the current assets/current liabilities ratio is expected in this study. The earnings before interest and tax/total assets ratio is the profitability measure given by the earnings before interest and tax divided by the total assets book value. Jacobs Jr. (2010) showed that profitability, as measured by the profit margin, is negatively associated with the CCF. Therefore, this study expects an inverse association between the CCF and the ratio of earnings before interest and tax/total assets.

In this study, the gross national income per capita growth, the growth rate of the real GDP, the rate of inflation, the public debt, the budget balance and the rate of unemployment are presented as the CCF's candidate macroeconomic drivers. Jimenez, Lopez and Saurina (2009) revealed an inverse association between the real GDP growth and the usage of the credit line. Thus, the study expects an adverse relationship between the growth rate of the real GDP and the CCF. The gross national income per capita growth, the rate of inflation, the public debt, the budget balance and the rate of

unemployment are a proxy for broader financial and economic conditions that could escalate the designed model's forecasting ability. A negative correlation between the CCF and the gross national income per capita growth is expected. Nonetheless, this study anticipates a positive correlation between the CCF and each of the following four macroeconomic variables; the inflation rate, the public debt, the budget balance and the unemployment rate.

To reduce bias and increase precision, missing values are imputed instead of excluding the sample observations with missing values. Mean imputation is applied because it is not time-consuming and computationally demanding and it preserves the size of the sample (Song and Shepperd 2007). In this approach, the mean of the non-missing values for each determinant with missing value(s) is computed. Each missing value is then replaced by the computed mean for that determinant. The firm's age and the time with the bank are each missing 1.09% of their values, converting into 2.17% of corporations with missing values. Outliers can considerably bias the computed model parameters and lead to unbecoming inferences. To avoid the exclusion of extreme data points from the sample data, outliers are winsorised at the distribution's 1st and 99th percentiles.

6.5 Empirical results and analysis

This section provides a profound examination of the results of this study. The performance indicators for the designed models are also reported in this section. Statistically significant covariates are nominated by implementing a stepwise selection method with forward elimination premised on a 5% α-level. In this study, 0.15 is used as an entry probability and 0.20 is used as a removal probability in stepwise selection, as recommended by Hosmer and Lemeshow (2000), in order to incorporate all significant drivers of the CCFs. The study proposes two stepwise OLS models based on different mixtures of firm characteristics, account features and macroeconomic variables. Model 1 includes firm-specific characteristics and account-specific features and model II includes firm features, account characteristics and macroeconomic factors.

6.5.1 Model I

Table 6.2 outlines the coefficient estimates for the predictor variables incorporated into model I based on the training sample.

Table 6. 2 Coefficient estimates for variables included in model I

Variable	Coefficient estimate	SE	p-value
Constant	0.433	0.036	<0.001
CA	3.96E-05	2.17E-06	<0.001
TTD	0.137	0.005	<0.001
DA	-1.74E-0.5	1.15E-06	<0.001
DP	-0.117	0.036	<0.001
TA	-2.37E-0.5	2.11E-06	<0.001
CLV	-1.88E-0.5	1.29E-06	<0.001
BD/TA	0.210	0.043	<0.001
CA/CL	-0.107	0.036	0.003
EBIT/TA	-0.090	0.022	<0.000

SE denotes standard error. See Table 6.1 for ratio definitions.

The experimental findings indicate that all covariates included in model I are considerably related to the CCF for defaulted Zimbabwean privately-held non-financial firm credit lines, with the ratio of earnings before interest and tax/total assets, the current assets/current liabilities ratio, the collateral value, the total assets, the drawn amount and the credit usage (%) having a negative effect on the CCF, and the bank debt/total assets ratio, the time to default and the committed amount having a positive impact on the CCF.

In agreement with the studies of Brown (2012) and Jacobs Jr. (2010), this experiment confirms that the committed amount is positively associated with the CCF, showing that the greater the committed amount, the greater the CCF. This finding is unsurprising given that since 2016 Zimbabwe has been experiencing severe liquidity challenges which emanated from the relinquishment of its local currency, the Zimbabwean dollar, in 2009. Due to the restricted liquidity in financial markets, several Zimbabwean

privately-traded corporations have been increasing their credit line limits as they use credit lines as one of their major sources of liquidity. This implies that the more the corporations are credit and/or liquidity restricted, the greater the likelihood that the credit limit rises and the bigger the percentage growth in the magnitude of the credit line limit. Since borrowers race to withdraw on their credit lines during distressed economic and financial conditions (see, for instance, Luo and Murphy, 2020), the CCF for credit lines with high committed amounts is augmented. However, some studies indicated that bigger credit lines are withdrawn less since banks may thoroughly monitor credit lines with larger commitment sizes (see, for instance, Zhao, Dwyer and Zhang, 2014), thereby reducing their CCFs.

This study reveals that the time to default is a significant determinant of the CCF. The time to default enters model I with a positive sign, as anticipated. Therefore, the prolonged time to default is linked to higher CCF values. During economic downturn conditions, there are more (less) opportunities of balance and limit increases (decreases) with extended time to default. Jacobs Jr. (2010) posited that longer time horizons to default are associated with augmented chances for clients to withdraw from their lines of credit. The positive correlation between the time to default and the CCF is also supported by Tong et al. (2016).

As expected, the bank debt/total assets ratio has a positive sign. This designates that as the bank debt/total assets ratio rises, the CCF increases. In agreement with this finding, Jacobs Jr. (2010) discovered a noteworthy positive correlation between the ratio of bank debt/total assets and the CCF. Zimbabwean privately-owned firms are often undercapitalised. As a result, they are highly levered since they mainly use bank debt to finance their working capital needs and growth. High leverage makes it difficult for private corporations to obtain supplementary funding from other sources other than withdrawing from their credit lines. Using the same reasoning line, Zhao, Dwyer and Zhang (2014) indicated that high levered firms find it challenging to get extra funding besides withdrawing on their credit lines. Further, during the observation time, the Zimbabwean government presented the ‘Buy Zimbabwe’ and ‘Make Local Buy Local’ campaigns and barred some imports to circumvent local corporations' failure by stimulating demand for home-grown goods and services. The augmented demand for local goods and services exposed numerous private corporates to aggressive growth periods. This aggressive growth of corporations and the associated uncertainty involved in these investment prospects further encouraged higher usage of the credit lines. Zhao,

Dwyer and Zhang (2014) and Agarwal, Ambrose and Liu (2006) highlighted that companies' aggressive growth promotes higher credit line usage. Moreover, Zimbabwean privately-held firms often pool their bank debt from a number of banks. Due to coordination difficulties between banks and owing to their economic inducements at the summit of firms' capital structure, the frontiers of optimal foreclosure have been fixed higher than otherwise, resulting in higher CCFs. This revelation is supported by Carey and Gordy (2007). However, Jacobs Jr. (2010) found that highly levered corporates, as indicated by the long-term debt/market value of equity ratio, maybe under closer scrutiny and have less ability to withdraw more funds from their credit lines in the race to default, resulting in low CCF.

Consistent with the finding of Jacobs Jr. (2010), this study reveals that the drawn amount is negatively related to the CCF, indicating that the larger the drawn amount, the smaller the CCF. This result emanates from the fact that under distressed economic and financial conditions in which chronic liquidity challenges are the order of each day, defaulted privately-held firms would have already withdrawn more from their lines of credit as at 12 months prior to default. Nevertheless, Tong et al. (2016) included the drawn amount as a determinant of CCF in their experiment and discovered that it is positively associated with the CCF.

The study finds that the drawn percentage or credit usage has an inverse relationship with the CCF, reflecting that as the credit usage increases, the CCF falls. This discovery is in agreement with the research outcomes of Tong et al. (2016), Brown (2012) and Jacobs Jr. (2010). One explanation for this finding is that defaulted corporations would already have drawn more from their credit lines as at 12 months before default. Moreover, lenders usually notice the obligors' worsening creditworthiness during distressed economic and financial conditions and reduce their credit line limits accordingly, growing the utilisation ratios in that way and thereby reducing the CCFs. Zimbabwean banks cut, though infrequently, partly or wholly unutilised credit lines, henceforth reducing the chances of privately-traded corporations withdrawing more from their credit lines and decreasing the consequential costs. In support of this observation, Pelzl and Valderrama (2019) indicated that liquidity challenges during the crisis periods adversely impact on banks' supply of credit lines since banks considerably cut partially or entirely unexploited credit commitments at the peak of the crisis. Luo and Murphy (2020) argued that the bank’s motivation is to halt or reduce the borrower’s credit as soon as it detects or assumes a substantial rise in credit risk. Nonetheless, Luo

and Murphy (2020) and Barakova and Parthasarathy (2013) posited that banks are only partially effective in cutting off or decreasing credit lines for borrowers, which ultimately default. Qi (2009) observed that obligors are more likely to withdraw additional funds in the race to default, but lenders rarely reduce the limits of credit lines and occasionally increase limits of credit lines, although less regularly.

As a firm size measure, the total assets book value has a negative sign, indicating that the CCF is reduced for larger company sizes meaning that the greater the firm's size, the lesser the CCF. The first justification for this outcome is that bigger corporates are associated with several financing sources, while small companies habitually count on the funding from their banks. Consequently, smaller corporations withdraw more from their lines of credit than huge firms under economic downturn conditions. This observation is supported by Zhao, Dwyer and Zhang (2014). Secondly, huge corporates are associated with superior credit quality, resulting in an adverse association between the CCF and the company size. In the same vein, Jimenez, Lopez and Saurina (2009) suggested that big firms are usually characterised by superior quality, causing an adverse association between the corporate size and the credit utilisation. Nevertheless, the negative relationship between the firm size and the CCF is not in agreement with Jacobs Jr. (2010), who proposed that the CCF is positively correlated with huge corporate size. The author articulated that huge corporations are associated with high CCF values since less effort and resources are used to analyse such borrowers' creditworthiness and to monitor them or they are exposed to less deterring terms.

In this study, it is discovered that the collateral value is a significant driver of the CCF. Collateral value has a negative sign, as expected. This shows that the CCF is reduced for credit lines with high collateral values and the CCF is increased for credit lines with low collateral values. Withdrawals from secured lines of credit are restricted due to amplified controls. The economic import of this observation is that higher collateral values mitigate exposure at default risk. In the same line of thinking, Jimenez, Lopez and Saurina (2009) posited that collateralised credit lines are associated with slightly lower usage rates than uncollateralised lines, indicating low exposure at default values for collateralised lines of credit. Zhao, Dwyer and Zhang (2014) articulated that if a corporation has collateralised and uncollateralised credit lines, it has inducements to withdraw more on the uncollateralised credit lines. On the other hand, Zhao, Dwyer and Zhang (2014) proffered the argument that corporates with uncollateralised credit lines are characterised by lower usage as compared to those with collateralised credit lines.

One possible reason for this outcome is that banks watch line usage of uncollateralised credit lines more carefully since the loss given default could be greater (Zhao, Dwyer and Zhang, 2014). Zhao, Dwyer and Zhang (2014) further highlighted that banks usually grant unsecured credit lines to obligors with elongated lending relationships or lesser risk, resulting in low credit line usage. Using the same line of reasoning, Jacobs Jr. (2010) found a positive association between the collateral rank and the CCF. The authors further proposed that loans with superior collateral rank are under a less degree of scrutiny.

As a profitability mark, the ratio of earnings before interest and tax/total assets is inversely related to the CCF, as anticipated. This indicates that the greater the earnings before interest and tax/total assets ratio, the lower the CCF and the lower the ratio of the earnings before interest and tax/total assets, the higher the CCF. This finding is not surprising given that unprofitable corporates regularly withdraw more from their credit lines than the profitable ones, resulting in lower (higher) CCF values for profitable (unprofitable) corporates. Profitable firms have a number of funding sources at their disposal and are characterised by superior credit quality, resulting in reduced credit line usage. In the same vein, Zhao, Dwyer and Zhang (2014) propounded that bad financial performance of a corporate can make it burdensome for the firm to obtain supplementary funds besides withdrawing from their credit lines. Jimenez, Lopez and Saurina (2009) suggested that profitable corporations are typically characterised by superior credit quality, leading to an inverse relationship between their credit line usage and profitability.

The empirical results of this study reveal that the CCF is reduced for augmented liquidity, as measured by the ratio of current assets/current liabilities, reflecting that the bigger the current assets/current liabilities ratio, the lower the CCF. This result is reasonable given that in most cases, in their journey to default, more liquid corporates withdraw less from their credit lines, while liquidity constrained corporations withdraw more from their credit lines. Liquid firms have alternative sources of funding besides credit lines at their disposal and are associated with superior credit quality, which results in low credit line utilisation rates. Consistent with this finding, Jacobs Jr. (2010) discovered a significant inverse correlation between the current ratio and the CCF. Zhao, Dwyer and Zhang (2014) confirmed that firms with liquidity challenges could find it difficult to get further funding besides withdrawing from their credit lines, thereby increasing their credit line utilisation ratios. Zhao, Dwyer and Zhang (2014)

showed that through the provision of credit lines, banks were counted as one of the prominent suppliers of liquidity for privately-owned corporates at the apex of the recent 2007 – 2008 world-wide recession. Kaplan and Zingales (1997) also noted that liquidity constrained corporates withdraw more from their lines of credit. Moreover, Jacobs Jr. (2010) observed that liquid corporates are associated with lower exposure at default values while Jimenez, Lopez and Saurina (2009) proffered the argument that liquid corporations are commonly characterised by superior credit quality, resulting in a negative correlation between their credit line utilisation and liquidity.

6.5.2 Model II

Model II results are indicated in Table 6.3.

Table 6. 3 Coefficient estimates for variables included in model II

Variable	Coefficient estimate	SE	p-value
Constant	0.447	0.034	<0.001
CA	4.32E-05	3.99E-06	<0.001
DP	-0.120	0.037	<0.001
DA	-1.90E-05	1.01E-06	<0.000
TTD	0.203	0.043	<0.001
TA	-3.10E-05	2.97E-06	<0.00
BD/TA	0.175	0.005	<0.001
CA/CL	-0.152	0.011	<0.000
EBIT/TA	-0.039	0.011	<0.000
RGDP	-0.058	0.010	<0.000
INF	-0.040	0.018	0.028

SE denotes standard error. See Table 6.1 for ratio definitions.

The empirical findings show that all the predictors included in model II are considerably correlated with the CCF for the defaulted Zimbabwean privately-controlled non-financial firm credit lines with the real GDP growth rate, the current assets/current liabilities ratio, the earnings before interest and tax/total assets ratio, rate of inflation, the total assets, the drawn amount and the credit usage having an inverse influence on the CCF, and the bank debt/total assets ratio, the time to default and the committed amount having a positive effect on the CCF. It is observed that the signs for the estimated coefficients for the committed amount, the time to default, the drawn amount, the credit usage, the total assets, the bank debt/total assets ratio, the earnings before interest and tax/total assets ratio and the current assets/current liabilities ratio are similar to those in model I. Two macroeconomic variables are included in model II, namely, the inflation rate and the real GDP growth rate. In model II it is observed that the collateral value which is significant in model I is dropped by the stepwise selection technique. One possible reason for this is the fact that its association with the CCF is reflected by the macroeconomic variables since macroeconomic factors directly affect collateral values.

As expected, the growth rate of the real GDP has an inverse association with the CCF, indicating that an uptick in the growth rate of the real GDP is characterised by a fall in the CCF, and a drop in the real GDP growth rate is linked to an increase in the CCF. This outcome is unsurprising given that real GDP is a measure of economic growth. During economic downturn conditions, obligors facing financial restraints withdraw more funds from their credit lines to withstand these adverse conditions, resulting in increased CCF values. Using the same line of reasoning, Zhao, Dwyer and Zhang (2014) postulated that corporations are more probable to withdraw from their credit lines in order to withstand economic downturns. In Zimbabwe, credit lines are mainly implemented as liquidity sources by corporations. This observation is supported by Sufi (2009), who articulated that credit lines are an insurance mechanism for corporations. Jimenez, Lopez and Saurina (2009) incorporated the real Spanish GDP growth as a predictor in their study and revealed that it is negatively correlated with the credit line utilisation. Further, Qi (2009) articulated that higher exposure at default values characterise downturn economic conditions, signifying that downturn conditions are associated with high utilisation rates. However, Zhao, Dwyer and Zhang (2014) and Qi (2009) posited that banks usually tighten credit during recessions, resulting in lower usage of credit lines and, ultimately, exposure at default. Zhao, Dwyer and Zhang

(2014) further promulgated that fewer growth prospects or corporate downsizing during distressed economic and financial conditions may result in lower usage of credit lines. Moreover, Barakova and Parthasarathy (2013) and Jacobs Jr. (2010) revealed that downturn periods are not characterised by higher exposure at default, suggesting that credit line utilisation is not as high as anticipated.

This study does not have a prior expectation of the negative association between the rate of inflation and the CCF. The coefficient for the inflation rate has a negative sign, indicating that as the inflation rate rises, the CCF falls. This finding seems counterintuitive. However, the possible explanation for this finding is that the sample period under review has been associated with an episode of deflation. In an economy, deflation stifles economic activity, increases unemployment rates, represses investment and leads to an increase in debt's real value (see, for instance, Mahonde, 2016). Masiyandima et al. (2018) argued that the emergence of the American dollar as the primary currency in Zimbabwe led to negative and low inflation rates, which adversely impacted on the country's growth. Firms find it more challenging to settle their debt commitments due to an increase in the real value of debt and money. Also, falling prices depress spending as customers postpone their purchases in anticipation of lower prices, resulting in firms getting lower revenue. Therefore, firms end up withdrawing more from their credit lines in order to meet their working capital and investment needs, resulting in higher CCF values. Deflation also aggravated the distressed economic and financial conditions in Zimbabwe and caused a deflation spiral. For instance, delayed spending generated more deflationary forces in the economy.

6.5.3 Performance metrics

The study applies the root mean squared error (RMSE), Pearson's correlation coefficient (r), coefficient of determination (R^2), and Spearman's correlation coefficient (α) (see Table 6.4) to assess and compare the in-sample predictive performance of the designed models. These performance metrics measure either calibration or discrimination. Calibration indicates how close are observed values to actual values, while discrimination involves giving an ordinal ranking of the response variable considered. Some performance metrics, such as R^2 and RMSE, that are used to assess the prediction performance of the designed OLS models may not be very necessary and must be interpreted with caution since one of the classical assumptions of OLS regression (i.e.,

there is a random sampling of observations) is violated, which raises questions about the unbiasedness of OLS regression coefficients. However, the values of these performance metrics are reported for comparative purposes. Therefore, the focus of this study on the prediction performance of OLS models is limited. With this in mind, the main focus of this research project is on identifying and interpreting the CCF determinants for the defaulted privately-owned corporates with credit lines.

Table 6. 4 Performance metrics for exposure at default models

Metric	Measure	Worst	Best
RMSE	Calibration	$+\infty$	0
R^2	Discrimination	0	1
α	Discrimination	0	
r	Discrimination	0	1

The RMSE refers to the square root of the mean of the squared difference between the forecasts and observations and it is described by

$$\text{RMSE} = \sqrt{\frac{1}{l}\sum_{i=1}^{l}(f(x_i) - y_i)^2}.$$

The Pearson's correlation coefficient refers to the summation of the products of the standard scores of the actual and forecasted values divided by the degrees of freedom. It is described by

$$\text{r} = \frac{1}{l-1}\sum_{i=1}^{l}\left(\frac{y_i-\bar{y}}{s_y}\right)\left(\frac{f(x_i-\bar{f})}{s_f}\right),$$

where $\bar{y}$ is the average of the actual values, $\bar{f}$ denotes the mean the predicted values, s_y represents the standard deviation of the actual values, and s_f is the standard deviation of the predicted values. The Pearson's correlation coefficient assumes the values between +1 (showing perfect positive correlation) and -1 (indicating perfect negative correlation) with 0 showing no correlation.

The Spearman's correlation coefficient is the Pearson's correlation coefficient employed to the rankings of the forecasted and actual values. It is given by

$$\alpha = 1 - \frac{6\sum_i^l d_i^2}{l(l^2-1)},$$

where d_i denotes the variance between the ranks of actual and estimated values. Basically, the Spearman's correlation coefficient assumes the values between +1 (showing perfect positive correlation) and -1 (indicating perfect negative correlation) with 0 indicating no correlation.

The coefficient of determination refers to 1 minus a portion of unaccounted variance as indicated below

$$R^2 = 1 - \frac{SS_{err}}{SS_{tot}},$$

where $SS_{tot} = \sum_{i=1}^{l}(y_i - \bar{y})^2$, $SS_{err} = \sum_{i=1}^{l}(y_i - f(x_i))^2$ and $\bar{y}$ represents the average of the actual CCF value.

The performance measures for CCF models are reported in Table 6.5.

Table 6. 5 Performance measures for CCF models

Metric	**Model I**	**Model II**
RMSE	0.4068	0.3518
R^2	0.2163	0.2598
α	0.4253	0.5388
r	0.4891	0.4150

The results show that, using the R^2 as the performance measure for the CCF models, model II is a better performing model than model I with the R^2 value of 0.2598. This indicates that incorporating macroeconomic variables into CCF models improves their predictive performance. In this study, it is observed from the empirical results that the R^2 values for the CCF models are generally low. However, these R^2 values can be compared to some R^2 values reported previously in other studies on loss given default

and exposure at default modelling (see, for instance, Brown, 2012, 2011, and Matuszyk, Thomas and Mues, 2010).

Given the predicted values for the CCFs obtained from the designed OLS models, the loan account level exposure at default estimates are deduced according to this equation:

Exposure at default = Present withdrawn amount + CCF x Present undrawn amount.

This equation produces the estimated value of the "monetary exposure at default" that can be compared to the observed value of exposure at default given in the dataset. Table 6.6 reports the forecasting performance of the predicted exposure at default values against the observed exposure at default values.

Table 6. 6 Exposure at default predictions premised on CCF estimates against observed exposure at default estimates

Metric	**Model I**	**Model II**
R^2	0.6977	0.7283
α	0.7396	0.7674
r	0.7875	0.8117

A captivating conclusion that can be derived from Table 6.6 is that, even though the estimated CCF values produce frail performance, when these values are implemented in the computation of the predicted exposure at default, a substantial improvement in the performance metrics is observed. This observation is in line with the finding of Brown (2012, 2011).

6.6 Conclusion

In this chapter, OLS regression models based on different amalgamations of borrower characteristics, account features, and macroeconomic variables were designed to estimate the CCF in order to precisely predict exposure at default at the account level for defaulted private non-financial corporations having credit lines under distressed economic and financial conditions in a developing economy. The key focus of this chapter was on identifying and interpreting the CCF determinants for the defaulted

privately-owned corporates with credit lines. Employing a unique real-life cross-sectional data set of defaulted credit lines for private corporations pooled from an anonymous Zimbabwean commercial bank over the observation period 2010 to 2018 to fit the models, the study discovered that a model that includes four account-specific, four firm-specific, and two macroeconomic variables is associated with the superior in-sample prediction performance as indicated by R^2. In particular, the study found a negative effect of the credit usage, the drawn amount, the total assets, the current ratio, the earnings before interest and tax/total assets ratio, the real GDP growth rate, and the inflation rate, and a positive effect of the committed amount, the time to default, and the ratio of bank debt/total assets on the CCF.

The empirical results indicate that accounting information is vital in analysing the CCF for defaulted private corporations with credit lines under downturn conditions in a developing country. Also, this study reveals that the in-sample forecasting results of CCF models and the corresponding exposure at default estimates are augmented by including macroeconomic variables. Another captivating conclusion is that even though the CCF's forecasting ability is frail, the study discovered from the experimental results that when this forecasted CCF value is implemented in the exposure at default framework to estimate the actual exposure at default value, a substantial improvement in performance metrics is observed.

This study can be extended in numerous ways. One dimension is to adopt a vast data set pooled from a number of financial institutions over a more extended time period. A benchmarking study, including a number of exposure at default techniques, may be conducted to give a better understanding of any improvements that can be made over an OLS regression model. Specifically, techniques that directly model exposure at default could be designed and compared with the exposure at default conversion measures. Future research effort is also required in comparing the performances of the fixed-horizon, variable-horizon, and cohort approaches in the computation of the CCF and estimation of exposure at default. Although, in practice, it is a common exercise to disregard the impact of censored CCF data on the coefficients of regressors, the nature of censored CCF distributions makes OLS regression models possibly inappropriate. Therefore, models for censored data could be assumed in modelling censored CCF data in order to improve the forecasting capabilities of the models. Further, more relevant determinants of the CCF could be pooled to improve the models' prediction ability.

After modelling default probability (see chapters three and four), workout recovery rates (see chapter five) and exposure at default (see chapter six), the next chapter, i.e., chapter seven, presents the thesis summary, conclusions and recommendations.

Chapter 7: Summary, Conclusions and Recommendations

7.1 Introduction

The AIRB approach allows financial institutions to compute their regulatory capital requirements using their forecasts of default probability, rate of recovery and exposure at default. This PhD thesis designed default probability, rate of recovery and exposure at default models for privately-controlled non-financial corporations under downturn conditions in a developing country (Zimbabwe). The key emphasis of this study was to recognise and interpret the covariates of default probability, recovery rate and CCF for Zimbabwean private non-financial corporations under downturn conditions.

This chapter is arranged as indicated below. Section 7.2 outlines the summary and conclusions drawn from the thesis, that is, from chapters two to six, section 7.3 describes the major findings, implications, contributions and recommendations of the study and section 7.4 presents areas for further research.

7.2 Thesis summary and conclusions

In chapter one of this research project, it was revealed that in the domain of corporate credit risk modelling, most studies were devoted to credit risk modelling for publicly listed companies in developed economies, owing to the extensive obtainability of dependable and wide-ranging data. Credit risk modelling literature for privately-owned corporations is generally limited, and that for such corporates in undeveloped economies is even more limited. The existing literature on private firm credit risk modelling is principally devoted to advanced economies. Corporate credit risk is considerably affected by macroeconomic variables. Hence, since the outburst of the recent 2007 – 2008 universal financial and economic meltdown, corporate credit risk modelling under distressed economic and financial conditions has been receiving a lot of regulatory and scientific attention the world over. Therefore, this study created default probability, rate of recovery and exposure at default models for Zimbabwean privately-held non-financial corporates under distressed financial and economic conditions.

Implementing an Arksey and O'Malley (2005)'s scoping review structure, chapter two of this thesis carried out a review of literature on bankruptcy prediction for private non-

financial corporates in undeveloped economies. The scoping review examined the reasons and motives for, emerging trends and research gaps in modelling bankruptcy risk for private corporations in developing countries. The chapter concluded that the prediction of the bankruptcy probability for private corporates in undeveloped markets is a crucial discipline that has not been properly studied and has some distinctive and unexplored zones due to its complexity, and the diverse business ethos of privately-owned corporations.

In chapter three, the study proposed stepwise logit models founded on diverse combinations of accounting ratios, firm and loan features and macroeconomic factors, and used the stepwise selection of some threshold criteria to predict default for Zimbabwean privately-owned non-financial firms under downturn conditions twelve months in advance. The key focus of chapter three was on the economic interpretation of the estimated coefficients of the drivers incorporated into the developed models. Using a unique data set of defaulted and non-defaulted Zimbabwean private non-financial corporations, the study revealed that a technique that includes five accounting ratios combined with one firm characteristic and two macroeconomic factors best explains the probability that a Zimbabwean private corporate defaults. Specifically, the study discovered a negative effect of the ratio of earnings before interest and tax/total assets, the ratio of (current assets-current liabilities)/total assets, the age of the firm, the real GDP growth rate and the rate of inflation on the default probability, and a positive effect of the bank debt/total assets, earnings before interest and tax/total liabilities and accounts receivable/net sales ratios on the default probability.

The experimental results indicate that it is feasible to forecast default probability for private non-financial firms under distressed financial and economic conditions using accounting information. Although default detection models with firm and loan characteristics and financial ratios performed well in predicting default for Zimbabwean private firms, the study provided evidence showing that a default prediction model that supplements loan and firm characteristics and financial ratios with macroeconomic variables was associated with a superior in-sample classification rate. This study highlights that the prediction ability of default models improves when macroeconomic factors are incorporated. The omnibus tests, Hosmer–Lemeshow tests and pseudo R^2 measures (Nagelkerke R^2 and Cox and Snell R^2) were used to analyse the goodness-of-fit of the designed techniques. These measures of goodness-of-fit indicated that the

designed techniques were fitted well to the data and the incorporated predictors were statistically significant.

In chapter four, the study proposed and analysed stepwise logistic regression techniques premised on diverse mixtures of financial ratios, firm and loan features and macroeconomic factors to separately detect default probability for audited and unaudited Zimbabwean private non-financial corporations under financial and economic stress twelve months in advance. This principal focus of chapter four was on identifying and interpreting the coefficients of the selected drivers of probability of default. Implementing unique data matrices of defaulted and non-defaulted audited and unaudited Zimbabwean privately-traded corporations, this thesis offered considerable evidence indicating that models incorporating firm and loan characteristics, macroeconomic factors and accounting information best explain the probability of default for audited and unaudited Zimbabwean privately-held corporations. In particular, the study discovered a negative influence of the (current assets-current liabilities)/total assets ratio, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate, the rate of inflation and the net sales/net sales last year ratio and a positive effect of the bank debt/total assets, earnings before interest and tax/total liabilities, short-term debt/total assets and current assets/total assets ratios on the default probability for audited Zimbabwean private firms. Nevertheless, the study discovered a negative impact of the (current assets-current liabilities)/total assets ratio, the earnings before interest and tax/total assets ratio, the time with the bank, the real GDP growth rate and the rate of inflation, and a positive effect of the earnings before interest and tax/total liabilities, short-term debt/total assets, net sales/net sales last year and current assets/total assets ratios and the interest rate on the default probability for unaudited Zimbabwean private firms.

Chapter four results show that accounting information is useful in differentiating between audited and unaudited private firms in default and those not in default in the context of distressed financial and economic conditions. The study also indicates that the incorporation of macroeconomic factors improved model fit and the prediction performance of default models. Further, the study confirms that the determinants of default probability for audited and unaudited privately-traded corporations are not the same. In chapter four, the omnibus tests, Hosmer-Lemeshow tests and pseudo R^2 measures (Nagelkerke R^2 and Cox and Snell R^2) were implemented to examine the goodness-of-fit of the created models. These goodness-of-fit measures indicated that the

designed techniques were fitted well to the data and the incorporated predictors are statistically significant.

In chapter five, the study suggested stepwise OLS models premised on diverse combinations of firm characteristics, loan features and macroeconomic variables to forecast recovery rates for defaulted private non-financial corporate bank loans under economic and financial stress in Zimbabwe. The principal research focus of chapter five was on the identification and economic interpretation of the predicted coefficients for the determinants incorporated into the designed models. Applying a distinctive data matrix of defaulted private non-financial firm bank loans, this study revealed that a model that incorporates four account-specific, four firm-specific and two macroeconomic variables is associated with the superior in-sample prediction performance. In particular, the study found a negative effect of the exposure at default, the length of the workout process, the total debt/total assets ratio and the interest rate on the recovery rates, and a positive impact of the firm size, the earnings before interest and tax/total assets ratio, the (current assets – current liabilities)/total assets ratio, the collateral value, the rate of inflation and the real GDP growth rate on the recovery rates. In this chapter, it is revealed that accounting information is useful in examining recovery rates for private corporations under downturn conditions. The study also discovers that the prediction results of recovery rate models are amplified by incorporating macroeconomic variables. The research project used the MAE, RMSE, R^2 and the Spearman's correlation coefficient to examine and discriminate the forecasting capacity of the designed recovery rate models. Although the model fit was weak across the designed models as shown by R^2, such values are typical in recovery rate modelling. The results produced in this analysis are comparable to the results revealed in other studies.

Finally, in chapter six, the study designed OLS regression models premised on diverse combinations of borrower features, account characteristics and macroeconomic factors to predict the CCF in order to accurately estimate, at the account level, exposure at default for defaulted Zimbabwean private non-financial corporations having credit lines under distressed economic and financial conditions. The main focus of chapter six was to identify and interpret the CCF determinants for the defaulted privately-owned corporates with credit lines. Employing a unique real-life data set of defaulted credit lines for private non-financial corporations, the study discovered that a model that includes four account-specific, four firm-specific, and two macroeconomic variables is

associated with the superior in-sample prediction performance. The study found a negative effect of the credit usage, the drawn amount, the total assets, the current assets/current liabilities ratio, the earnings before interest and tax/total assets ratio, the growth rate of the real GDP and the rate of inflation on the CCF, and a positive effect of the committed amount, the time to default, and the bank debt/total assets ratio on the CCF.

Chapter six indicates that accounting information is vital in examining the CCF for defaulted private non-financial corporations with credit lines under downturn conditions. The study also reveals that the in-sample forecasting results of the CCF models and the corresponding exposure at default estimates are improved by incorporating macroeconomic variables into the CCF models. The RMSE, R^2, Spearman's correlation coefficient and Pearson's correlation coefficient were implemented to evaluate the designed models' in-sample predictive performance. It was observed from the empirical results that the R^2 values for the CCF models are generally low. However, these R^2 values can be compared to some R^2 values reported previously in other exposure at default and loss given default modelling studies. Further, even though the CCF's forecasting ability was frail, the study discovered that when the forecasted CCF value is implemented in the exposure at default framework to forecast the actual exposure at default value, a substantial improvement in performance metrics is observed.

In summary, the thesis created default probability, rate of recovery and exposure at default models for Zimbabwean privately-held non-financial corporates under distressed financial and economic conditions as required by the AIRB. An extensive review of the drivers of probability of default, recovery rate and CCF for Zimbabwean privately-traded non-financial firms under downturn conditions was presented.

7.3 Key findings, implications, contributions and recommendations

After presenting the thesis summary and conclusions, the major findings, implications, contributions and recommendations of the thesis are identified as follows:

7.3.1 Conducting a scoping review of literature for private firm bankruptcy prediction in developing economies

In chapter two, a review of literature on bankruptcy forecasting for private firms in undeveloped economies was carried out using an Arksey and O'Malley (2005)'s scoping review framework. To the best of the researcher's understanding, this research project was the first piece of research work to perform a scoping review of literature on bankruptcy prediction for privately-owned non-financial corporations in developing countries. The scoping review examined the reasons and motives for research, the emerging trends and research gaps in forecasting bankruptcy probability for private corporates in undeveloped markets. It highlighted that the prediction of bankruptcy probability for private corporations in developing countries is an important discipline that has not been suitably scrutinised and has some distinctive and unexplored fields due to its complexity and the diverse business ethos of private firms. The results of this scoping review could be used as the basis for undertaking a full systematic review in this area of study.

The study discovered that it was crucial to forecast bankruptcy for private corporations in developing markets. Private corporates are the dominant legal forms of corporations in developing economies. Also, private corporations promote economic growth and development, stimulate financial and technological innovations and also reduce unemployment rates in developing economies. Corporate bankruptcy detection literature is mostly devoted to publicly-traded corporates in advanced markets for which data is widely obtainable; while little is known about the bankruptcy probability covariates for private corporations and very little is well-known for such corporates in undeveloped economies. Since publicly-traded firms and privately-owned corporations are not identical, bankruptcy detection models founded on data pooled from publicly-traded corporates and implemented to privately-owned corporations may likely misrepresent existent default risk since privately-owned firms and public corporates are dissimilar. Thus, this research project recommends building models that forecast bankruptcy probability for privately-held corporations, specifically for developing markets in order to get high classification rates.

Developing markets are associated with unique, unsophisticated economic and financial features. Therefore, simple models for forecasting corporate failure in an unsophisticated economic environment could do a more wonderful job than sophisticated corporate failure forecasting models created in advanced markets. Further,

since developed and developing markets are not the same, implementing corporate bankruptcy models founded on foreign data from developed countries to developing markets may not always offer trustworthy results because these models do not echo the economic, institutional and financial characteristics of developing markets. Moreover, developing markets are not entirely identical since they are associated with diverse economic, institutional and financial features. Hence, bankruptcy forecasting models created using economy-specific data are associated with high detection capability. Since developed and developing markets are different, and developing countries are not entirely similar, this research project recommends for the building of country-specific private corporate bankruptcy forecasting models in developing markets. The research project also found that the correlation between private firm bankruptcy probability and its covariates varies as settings change. Consequently, corporate bankruptcy forecasting models require to be recurrently revalidated and recalibrated in direct response to changes in situations in order to warranty that their forecasting ability does not deteriorate. How often the corporate bankruptcy prediction models are revalidated and recalibrated depends on the needs of individual banks. Researchers, practitioners and regulars are warned that when recalculating models they need to adopt the most recent data to get higher forecasting accuracy.

Categorising private corporations into non-failed and failed corporates is dependent on the 'corporate failure' definition implemented by the article since definitions of corporate failure are not standardised across markets. The definition of corporate failure applied influences the selection of predictor variables of bankruptcy probability for private firms. Nevertheless, there is no firm corporate failure definition in the financial markets and the measure of corporate failure is nominated subjectively in the existing literature. Thus, when comparing unique studies produced from various markets, it is critical to take into account the corporate failure definitions applied and when producing bankruptcy risk models for privately-traded firms in emerging markets, the implemented corporate failure definition need be plainly specified. In practice, there is a vital need to generate explicit private corporate model/s of bankruptcy for each form of corporate failure in developing countries.

It has emerged that corporations in emerging markets generally finance themselves chiefly using local currencies from local financial institutions in domestic financial credit markets, and their balance sheets have been increasingly leveraged. Further, in aggregate, corporations in developing markets have become less profitable. These

developments, among other issues, have a substantial influence on the probability of bankruptcy for privately-held corporations in undeveloped markets and are not a favourable situation for credit risk. The research project also discovered that even though the generation of bankruptcy detection models for privately-held corporates in developing markets is not a trivial exercise task owing to scant default data and information for privately-owned firms, of late, a little more attention has been directed to private firm bankruptcy detection owing to momentous enlargement of private corporate loan business, the presentation of Basel II/III frameworks, the upsurge in the obtainability of enormous private corporation default data and information databases and the advancement of statistical models that encourage credit risk dynamic modelling.

Several financial institutions have been demanding audited financial statements from the private corporations before offering them loans. From the perspective of lenders, private corporations with audited financial statements are associated with lower bankruptcy risk than their unaudited equivalents. Then, it is imperative to individually build bankruptcy detection models for audited and unaudited private corporates in developing markets from a credit risk management standpoint. In addition, a number of bankruptcy forecasting models for privately-held firms in developing markets are founded on accounting ratios. Nevertheless, the forecasting capability of typical accounting-based bankruptcy forecasting models has been deteriorating over the years. Therefore, supplementary covariates need to be included in the bankruptcy risk models, e.g., firm and loan characteristics, industry effects and macroeconomic variables, and non-traditional measures and big data, for example, history of payables, analysis of invoices, governance characteristics and inputs from the social media. Specifically, to precisely detect private corporate bankruptcy probability in the context of distressed economic and financial conditions, macroeconomic conditions typically captured by macroeconomic factors should be included in the models. This research study thus recommends the incorporation of both dynamic and comparative financial ratios when generating private corporate bankruptcy detection models for developing markets.

Nonetheless, there is no exact standard for selecting the requisite covariates in the private corporate bankruptcy detection sphere, and several models implement different predictor variables. Further, there is no accord among authors on which predictors are the best pointers of private corporation failure in developing markets. Therefore, it is essential to choose the preliminary set of covariates based on statistical contemplations or a theoretical structure or both when creating bankruptcy models for private

corporations in undeveloped markets. As a starting point, it is recommended that researchers should adopt variables that are popular in the extant literature, are relevant to the experiment and have superior predictive power in empirical research when predicting private firm bankruptcy, the intention being to improve the developed models' predictive capacity.

The research project discovered that multiple discriminant analysis is the most implemented method in private corporate bankruptcy forecasting in emerging economies. In particular, most studies are founded on the Altman's Z-score family of models. Although the Z-score models have proved to be remarkably resilient over the years (see, for instance, Altman, 2018), there is plentiful existent literature that demonstrates that the Z-score models are characterised by low forecasting abilities and are outshined by other competing techniques in forecasting bankruptcy for private firms in developing markets. Thus, to enhance bankruptcy model detection abilities, it is recommended to apply more sophisticated models which are extensively implemented in advanced markets in private corporate bankruptcy forecasting in undeveloped economies. Further, there is a great need to forecast private corporate bankruptcy probability in developing countries applying dynamic models that reveal the point that firms transmute over time and clearly give the expected failure time.

7.3.2 Probability of default forecasting

The significant contributions of the thesis set out in chapter three are as follows. Stepwise logistic regression models were developed, premised on diverse combinations of financial ratios, firm and loan features and macroeconomic factors, and a stepwise selection of some threshold criteria to forecast default probability for privately-held non-financial corporations under downturn conditions in a developing country (Zimbabwe). The chief goal of this chapter was to recognise and interpret the drivers of private firm probability of default. A number of new predictors were adopted in estimating probability of default and a comprehensive examination of the drivers used in the modelling of probability of default was given. For applicability and efficacy purposes, a unique real-world data set of Zimbabwean private non-financial firms was applied.

The experimental results indicated that accounting information is beneficial in distinguishing between defaulted and non-defaulted privately-held non-financial corporations under downturn conditions in a developing economy. This implies that

financial statements are imperative in forecasting default probability for private non-financial firms under distressed economic and financial conditions in a developing country. Further, the study indicated that the prediction results of probability of default models for privately-traded corporations are enhanced by including macroeconomic factors. This implies that firm-and-loan-information, accounting-data and macroeconomic-information based models best explain default probability for private non-financial firms under distressed economic and financial conditions in developing country. As a recommendation, firm and loan characteristics, macroeconomic factors and accounting information could be included in the models when forecasting probability of default for privately-held non-financial corporations under financial and economic stress in a developing economy. The incorporation of macroeconomic variables is vital since it allows stress testing of default probability of private firms. Probability of default forecasts could be implemented as inputs into expected and unexpected loss prediction techniques, regulatory and economic capital models, impairment predicting, stress testing of credit portfolios, pricing credit portfolios, and advising credit portfolio management, among other things.

7.3.3 Probability of default modelling for audited and unaudited firms

In chapter four, the study separately predicted probability of default for audited and unaudited Zimbabwean private non-financial corporates under downturn conditions implementing stepwise logit models premised on diverse combinations of financial ratios, firm and loan features and macroeconomic factors. The experiment's fundamental purpose was to identify and interpret the drivers of probability of default for audited and unaudited Zimbabwean privately-traded non-financial corporations. Several new predictor variables were employed in separately predicting probability of default for audited and unaudited private non-financial corporates and a comprehensive examination of the determinants applied in probability of default modelling for privately-traded non-financial firms was presented. To fit the models, the research project adopted two distinctive real-life data matrices of defaulted and non-defaulted audited and unaudited Zimbabwean privately-held non-financial corporations.

The study results showed that under downturn conditions, accounting information is vital in distinguishing defaulted and non-defaulted audited and unaudited Zimbabwean privately-traded non-financial corporates, and the forecasting ability of default probability models for privately-held non-financial corporates is improved by

incorporating macroeconomic variables. This implies that financial statements are vital in forecasting default probability for audited and unaudited private non-financial firms under distressed economic and financial conditions in a developing economy. Further, this implies that firm-and-loan-information, accounting-data and macroeconomic-information based models best explain default probability for audited and unaudited private non-financial firms under distressed economic and financial conditions in developing country. As a recommendation, firm and loan characteristics, macroeconomic factors and accounting information should be included when forecasting probability of default for audited and unaudited privately-traded non-financial corporations under distressed economic and financial conditions in a developing economy. The incorporation of macroeconomic variables is imperative since it allows stress testing of default probability of privately-held corporates. Additionally, the analysis disclosed that the determinants of default probability for audited and unaudited Zimbabwean privately-owned non-financial corporations are not the same. It is recommended to separately analyse the determinants of and develop models for default probability for audited and unaudited privately-traded non-financial corporates from a risk management standpoint. Default probability estimates could be used as inputs into expected and unexpected loss prediction techniques, impairment predicting, stress testing of credit portfolios, regulatory and economic capital models, pricing credit portfolios, and advising credit portfolio management, among other things.

7.3.4 Recovery rate prediction

The contributions of the study set out in chapter five are presented below. Stepwise OLS regression models were designed based on diverse combinations of firm characteristics, loan features and macroeconomic variables to predict workout recovery rates for defaulted bank loans for private non-financial corporations under distressed financial and economic conditions in Zimbabwe. The principal intention of this chapter was to identify and interpret the determinants of private firm defaulted bank loans recovery rates. Several new drivers were applied in forecasting the recovery rates and a broad analysis of the adopted determinants in modelling the recovery rates was set out. For suitability and efficacy determinations, a unique real-life data set of defaulted private firm bank loans was adopted.

The study revealed that accounting information is valuable in examining the recovery rates for defaulted bank loans for private corporations under downturn conditions in an undeveloped market. This implies that financial statements are crucial in predicting

recovery rates for defaulted bank loans for private non-financial firms under distressed economic and financial conditions in a developing country. Further, the thesis disclosed that the forecasting results of the recovery rate models are enhanced by incorporating macroeconomic variables. This implies that bank loans recovery rate models based on firm characteristics, loan features and macroeconomic variables best explain bank loans recovery rates for private non-financial firms under distressed economic and financial conditions in developing country. As a recommendation, firm characteristics, loan features and macroeconomic variables could be incorporated when forecasting workout recovery rates for private non-financial corporations under distressed economic and financial conditions in a developing country. The inclusion of macroeconomic variables is critical since it permits stress testing of loss given default or recovery rates of privately-held corporations. Loss given default or recovery rates forecasts could be adopted as inputs into expected and unexpected loss prediction techniques, regulatory and economic capital models, stress testing of credit portfolios, pricing credit portfolios, and advising credit portfolio management, among other things.

7.3.5 Exposure at default estimation

In chapter six, OLS regression models were designed premised on diverse mixtures of borrower features, account characteristics and macroeconomic factors to predict the CCF in order to accurately estimate, at the account level, exposure at default for defaulted private non-financial corporates having credit lines under downturn conditions in Zimbabwe. The primary emphasis of this chapter was on identifying and interpreting the covariates of the CCF for the defaulted privately-owned corporations with credit lines. Several new determinants were adopted in estimating the CCF and a comprehensive examination of the drivers implemented in the prediction of the CCF was outlined. For applicability and efficacy purposes, a unique real-life data set of defaulted Zimbabwean private corporations was employed.

It was observed that accounting information is essential in analysing the CCF for defaulted private corporations with credit lines under downturn conditions in a developing country. This implies that financial statements are vital in predicting CCFs for defaulted private non-financial corporations with credit lines under distressed economic and financial conditions in a developing market. Additionally, the thesis revealed that the CCF models' prediction results and the corresponding exposure at default estimates are improved by incorporating macroeconomic factors. This implies that CCF models based on borrower characteristics, account features and

macroeconomic variables best explain the CCF and the corresponding exposure at default for private non-financial firms under distressed economic and financial conditions in developing country. As a recommendation, borrower characteristics, account features and macroeconomic variables could be incorporated when forecasting the CCF and the corresponding exposure at default for private non-financial corporates under downturn conditions in a developing economy. The incorporation of macroeconomic factors is critical since it permits stress testing of exposure at default of privately-traded firms. Exposure at default forecasts could be used as inputs into expected and unexpected loss prediction techniques, regulatory and economic capital models, stress testing of credit portfolios, impairment predicting, pricing credit portfolios, and advising credit portfolio management, among other things.

7.3.6 Policy implications

The findings of this research project have a number of useful policy implications. For banks to create effective corporate credit risk models they need to design default probability, recovery rate (or loan given default) and CCF (or exposure at default) models which are specific to firm sub-categories such as private corporates, SMEs and public corporations. The modelling of credit risk for privately-traded non-financial corporations is imperative because it helps financial institutions create policies linked to the provision of credit and the cost of credit to private corporates, and assists in the designing of collection policies to be implemented for defaulted privately-traded non-financial firms and formulation of credit terms. Credit risk examination is crucial in generating the prices and yields of financial assets, and in preventing some of the costs related to bankruptcy. Further, the analysis of financial institutions' risk exposure towards privately-traded non-financial firms is of interest to macroprudential and microprudential supervisors in their quest to maintain stability, order and sanity in the financial sector and the economy at large. For instance, the issue of non-performing loans has become a nuisance and has been given high significance by policy makers such as central banks. The results of this thesis are vital for decision-makers in their expedition to stimulate macroeconomic growth and development. Given the financial and economic significance of privately-traded non-financial firms for the Zimbabwean economy, the results of this study also offer an economic validation for the separate assessment of credit risk for audited and unaudited privately-owned non-financial firms.

7.4 Issues for further research

Issues for further research emanating from the findings presented in chapters two to six are outlined in this section.

7.4.1 Scoping review of literature for private non-financial firm bankruptcy prediction in developing economies

For future research, scoping reviews can be conducted to disclose how common and promising models perform in bankruptcy forecasting for privately-owned corporates in developing economies using specific criteria. There is likelihood that the scoping review may have overlooked some appropriate articles. This omission may be attributed to the selection of databases, time restrictions, elimination of the gray literature from the review, i.e., literature not published, and the exclusion of articles published in other languages other than English. Therefore, this study could be extended by adopting and reviewing a huge number of research articles over a long period of time to better understand bankruptcy probability prediction for privately-traded firms in developing economies. Additional research articles could be identified through searching in other databases, inclusion of gray literature and incorporation of studies published in other languages other than English. This current scoping review provided sufficient evidence to justify the undertaking of a full systematic review in this area of study.

7.4.2 Probability of default

This research area may be extended by employing a vast data set and analysing the in-of-sample and out-sample results and classification rates of the models. Further, more sophisticated models such as machine learning and artificial intelligence models could be adopted and more suitable determinants could be pooled together to augment the prediction capacity of the techniques. The study on probability of default forecasting could also be extended to cover other financial products, such as mortgage loans, credit lines and agricultural loans.

7.4.3 Default probability for audited and unaudited private corporations

Firstly, this current research could be extended by implementing more sophisticated techniques, e.g., expert systems and machine learning, to augment the detection capability of the techniques. Secondly, to improve the generalisability of the results, massive data sets of audited and unaudited private firms may be adopted. Massive data sets could also enable the analysis of the out-of-sample and in-sample results and classification rates of the models. Thirdly, further studies could be conducted by combining more relevant drivers of private firm default probability to improve the

models' prediction capacity. Lastly, the examination could be stretched to cover other financial products, such as credit lines, mortgage loans and agricultural loans.

7.4.4 Recovery rate

For further research, the current study may be improved in several dimensions. The study implemented a restricted quantity of observations. This may introduce some bias in the estimation of recovery rates. Therefore, a vast sample data could be gathered and applied in the analysis of defaulted private non-financial firm bank loan recovery rates. By increasing the data set, further examinations on recovery rates' predictor variables for private firm defaulted bank loans under downturn conditions in developing countries can be done. Recovery rates systematically differ through time. Thus, dynamic models that consider time-varying changes systematically in the recovery rates can be employed. Also, more appropriate predictor variables in a time variant framework can be combined to improve the models' prediction capacity. Although, in reality, it is a common practice to neglect the effect of censored recovery rate data on the coefficients of regressors, the nature of censored recovery rate distributions makes OLS regression models possibly unsuitable. Therefore, models for censored data could be implemented in modelling censored recovery rate data in order to improve the forecasting abilities of the models. Further, the study could be stretched to cover other financial instruments such as revolvers, mortgage loans and agricultural loans.

7.4.5 Exposure at default

This study can be extended in numerous ways. One dimension is to adopt a vast data set pooled from a number of financial institutions over a more extended time period. A benchmarking study, including a number of exposure at default techniques, may be conducted to give a better understanding of any improvements that can be made over an OLS regression model. Specifically, techniques that directly model exposure at default could be designed and compared with the exposure at default conversion measures. Future research effort is also required in comparing the performances of the fixed-horizon, variable-horizon, and cohort approaches in the computation of the CCF and estimation of exposure at default. Although, in practice, it is a common exercise to disregard the impact of censored CCF data on the coefficients of regressors, the nature of censored CCF distributions makes OLS regression models possibly inappropriate. Therefore, models for censored data could be assumed in modelling censored CCF data in order to improve the forecasting capabilities of the models. Further, more relevant determinants of the CCF could be pooled to improve the models' prediction ability.

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Appendix A2.1: Title and abstract relevance screening form

	Assessment	Comments
1. Does the study examine bankruptcy risk for private non-financial firms in developing economies?	Yes ☐ No ☐ Can't tell ☐	
2. Does the study describe research in English?	Yes ☐ No ☐	

Reviewer Decision:

- The study will be incorporated for further screening and assessment, if the answer is "Yes" to both questions, i.e., 1 and 2.
- The entire study will be acquired for further evaluation and decision making at this stage, if the answer is "Can't tell" for question 1.

Appendix A2.2: Data characterisation form

Variable	Category	Explanation
1. Publication type	Journal article ☐ Book/Book chapter ☐ Thesis ☐ Report ☐ Conference Proceeding ☐ Other (Specify: ……)	
2. Author(s)/Year		
3. Country of data origin		
4. Study industry setting	Financial sector ☐ Non-financial sector ☐	
5. Does the study examine bankruptcy risk for private non-financial firms in developing economies?	Yes ☐ No ☐ Can't tell ☐	
ONLY carry on if the answer to question 5 is "Yes"		

6. Key characteristics of the study

Title of the study	Aim of the study	Variable(s) adopted	Sample	Technique (s)	Summary of results

Appendix A2.3: List of reviewed studies

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., and Suvas, A. (2017). Financial distress prediction in an international context: a review and empirical analysis of Altman's Z-Score model. *Journal of International Financial Management and Accounting* **28** (2), 131–171.

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Slefendorfas, G. (2016). Bankruptcy prediction model for private limited companies of Lithuania. *Ekonomika* **95** (1), 134-152.

Stojanovic, T., and Drinic, L. (2017). Applicability of Z-Score models on the agricultural companies in the Republic of Srpska (Bosnia and Herzegovina). *Agro-knowledge Journal* **18** (4), 227-236.

Takahashi, M., Taques, F. H., and Basso, L. (2018). Altman's bankruptcy prediction model: test on a wide out of business private companies sample. *iBusiness* **10** (1), 21-39.

Appendix A2.4: Cover page for the published article (chapter two)

Management Review Quarterly
https://doi.org/10.1007/s11301-021-00216-x

Check for updates

Bankruptcy prediction for private firms in developing economies: a scoping review and guidance for future research

Frank Ranganai Matenda[1] · Mabutho Sibanda[1] · Eriyoti Chikodza[2] · Victor Gumbo[3]

Received: 13 August 2020 / Accepted: 3 March 2021
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Abstract
The majority of studies on corporate bankruptcy detection are devoted to publicly-traded firms in advanced economies. Literature on bankruptcy prediction for private corporations is generally restricted and that for such corporates in undeveloped markets is even more limited. Existent evidence on privately-owned corporate bankruptcy forecasting is substantially dedicated to advanced countries. Implementing a scoping review structure of Arksey and O'Malley (Int J Law Manag 57:461–485, 2005), this paper carries out a review of literature concerning bankruptcy forecasting for privately-held firms in undeveloped economies. The main emphasis of the scoping review is to examine the reasons and motives for research, emerging trends and research gaps in modelling bankruptcy risk for private corporations in developing countries. The results of this scoping review show that the estimation of bankruptcy probability for privately-traded corporations in developing economies is a relevant discipline that has not been appropriately examined and has some unique and unexplored areas due to its sophistication and distinctive business ethos of private corporates.

Keywords Corporate bankruptcy prediction · Private firms · Predictor variables · Developing economies · Scoping review · Arksey and O'Malley (2005) framework

JEL Classification G32 · G33

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Extended author information available on the last page of the article

Published online: 27 March 2021

Appendix A3.1: Cover page for the published article (chapter three)

Journal of Credit Risk **17**(1), 1–27
DOI: 10.21314/JCR.2020.267

Risk journals

Research Paper

Corporate default risk modeling under distressed economic and financial conditions in a developing economy

Frank Ranganai Matenda,[1] Mabutho Sibanda,[1] Eriyoti Chikodza[2] and Victor Gumbo[3]

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Author: please check running head on odd pages – abbreviated form of title OK?

Changes to sentence OK?

(Received September 29, 2019; revised June 20, 2020; accepted August 23, 2020)

ABSTRACT

We create stepwise logistic regression models to predict the probability of default for private nonfinancial firms under distressed financial and economic conditions in a developing economy. Our main aim is to identify and interpret the drivers of private firm probability of default. For applicability and efficacy purposes, we apply a unique real-world data set of Zimbabwean private firms. Our experimental results show that the ratios of earnings before interest and tax (EBIT) to total assets, bank debt to total assets, EBIT to total liabilities, accounts receivable to net sales and the ratio of current assets minus current liabilities to total assets, the age of the firm, the real gross domestic product growth rate and the inflation rate are all strong drivers of probability of default for Zimbabwean private firms. We conclude that accounting information is useful in differentiating between defaulted and nondefaulted private firms under downturn conditions in a developing economy. Moreover, we determine that

Much of this paper has been slightly reworded for clarity, US English, journal style, etc. In addition, marginal queries have been added where major changes have been made or the meaning is unclear. Please check all text carefully throughout.

Corresponding author: F. R. Matenda

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Appendix A4.1: Cover page for the article in press (chapter four)

Default prediction for audited and unaudited private firms under economic and financial stress: evidence from Zimbabwe

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Abstract: This study develops stepwise logit models to predict default probability for audited and unaudited Zimbabwean non-financial privately-owned firms under downturn conditions. The research paper's main intention is to identify and interpret the predictors of default probability for audited and unaudited Zimbabwean private corporations. For pertinence and effectiveness reasons, the study applies two unique real-world datasets of defaulted and non-defaulted audited and unaudited private corporates. The findings of this study indicate that under downturn conditions, accounting information is imperative in differentiating defaulted and non-defaulted Zimbabwean private firms, and the predictive capacity of the private firm default models is augmented by including macroeconomic factors. Moreover, the study reveals that the drivers of default risk for audited and unaudited Zimbabwean private firms are dissimilar. As a recommendation, firm and loan characteristics, accounting information and macroeconomic variables must be incorporated when predicting default probability for private firms under downturn conditions.

Keywords: default probability; audited and unaudited private firms; economic and financial stress; developing economy; predictor variables; stepwise logit models.

Reference to this paper should be made as follows: Matenda, F.R.,

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Appendix A6.1: Cover page for the published article (chapter six)

Journal : SmallExtended 41283 | Article No : 71 | Pages : 27 | MS Code : 71 | Dispatch : 25-3-2021

Risk Management
https://doi.org/10.1057/s41283-021-00071-w

ORIGINAL ARTICLE

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Author Proof

Determinants of corporate exposure at default under distressed economic and financial conditions in a developing economy: the case of Zimbabwe

Frank Ranganai Matenda[1] · Mabutho Sibanda[1] · Eriyoti Chikodza[2] · Victor Gumbo[3]

Accepted: 13 March 2021
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Abstract

We design ordinary least squares (OLS) regression models to estimate the credit AQ1 conversion factor (CCF) in order to precisely predict the exposure at default (EAD) at the account level for defaulted private nonfinancial corporations having credit lines under distressed economic and financial conditions in a developing economy. Our primary focus is on identifying and interpreting the CCF determinants for the defaulted privately owned corporates with credit lines. We apply the models to a unique real-life cross-sectional dataset of defaulted Zimbabwean private corporations. Our empirical results show that the committed amount, the credit usage, the drawn amount, the time to default, the total assets, the ratio of bank debt to total assets, the current ratio, the EBIT to total assets ratio, the real gross domestic product growth rate, and the inflation rate are all substantial drivers of the CCF for Zimbabwean private corporates with credit lines. We observe that accounting information is essential in analysing the CCF for private corporations with credit lines under downturn conditions in a developing country. Furthermore, we reveal that the CCF models' forecasting results and the corresponding EAD estimates are augmented by including macroeconomic variables.

Keywords Exposure at default · Credit conversion factor · Private firm credit lines · Distressed economic and financial conditions · Developing economy · Ordinary least squares regression models

UNCORRECTED PROOF

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Extended author information available on the last page of the article

Appendix B: Editorial letter

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TO WHOM IT MAY CONCERN

Re: Confirmation of Editing of Frank Ranganai Matenda's (Student No: 217081687) Doctoral Thesis

This is to certify that I, Jairos Gonye (National Identity Number 27-049723-X-27), have edited **Frank Ranganai Matenda's** doctoral thesis with the title **Credit risk modelling for private firms under distressed economic and financial conditions in a developing economy: evidence from Zimbabwe** to be submitted to the **University of KwaZulu-Natal** in terms of the requirements for the attainment of a Doctor of Philosophy degree in Finance. My qualifications are as follows: PHDA (English) (University of Venda); MA (English) (University of Zimbabwe); BA (Hons) (English) (University of Zimbabwe) and Graduate Certificate in Education (Grad.CE) (University of Zimbabwe).

Thank you

[redacted] Date: 14/01/2021

Jairos Gonye (Associate Professor)
Head Technical Team: Journal of New Vision in Educational Research (JoNVER)
Great Zimbabwe University
Robert Mugabe School of Education and Culture

Appendix C: Ethical clearance certificate

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

01 October 2020

Mr Frank Ranganai Matenda (217081687)
School Of Acc Economics&Fin
Westville Campus

Dear Mr Matenda,

Protocol reference number: HSSREC/00001940/2020
Project title: Credit risk modelling for private firms under distressed economic and financial conditions: evidence from Zimbabwe
Degree: PhD

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 16 September 2020 in connection with the above, was reviewed by the Humanities and Social Sciences Research Ethics Committee (HSSREC) and the protocol has been granted **FULL APPROVAL** on the following condition:

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number. PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

This approval is valid until 01 October 2021.
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

All research conducted during the COVID-19 period must adhere to the national and UKZN guidelines.

HSSREC is registered with the South African National Research Ethics Council (REC-040414-040).

Yours sincerely,

[redacted]

Professor Urmilla Bob
(University Dean of Research)

/dd

Humanities and Social Sciences Research Ethics Committee
Postal Address: Private Bag X54001, Durban, 4000, South Africa
Telephone: +27 (0)31 260 8350/4557/3587 **Email:** hssrec@ukzn.ac.za **Website:** http://research.ukzn.ac.za/Research-Ethics
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INSPIRING GREATNESS

Appendix D: Turnitin report

Corporate credit risk modelling

ORIGINALITY REPORT

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