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Determinants of Default Probability for Audited and Unaudited SMEs under Stressed Conditions in Zimbabwe

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Abstract: Using stepwise logistic regression models, the study aims to separately detect and explain the determinants of default probability for unaudited and audited small-to-medium enterprises (SMEs) under stressed conditions in Zimbabwe. For effectiveness purposes, we use two separate datasets for unaudited and audited SMEs from an anonymous Zimbabwean commercial bank. The results of the paper indicate that the determinants of default probability for unaudited and audited SMEs are not identical. These determinants include financial ratios, firm and loan characteristics, and macroeconomic variables. Furthermore, we discover that the classification rates of SME default prediction models are enhanced by fusing financial ratios and firm and loan features with macroeconomic factors. The study highlights the vital contribution of macroeconomic factors in the prediction of SME default probability. We recommend that financial institutions model separately the default probability for audited and unaudited SMEs. Further, it is recommended that financial institutions should combine financial ratios and firm and loan characteristics with macroeconomic variables when designing default probability models for SMEs in order to augment their classification rates.

Keywords: default probability; distressed financial and economic conditions; unaudited and audited SMEs; determinants; stepwise logistic regression

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1. Introduction

Probability of default, exposure at default, and loss-given default are the most vital credit risk components. These components are implemented by financial institutions when they design risk policies, construct credit terms, determine required capital levels, price loans and do credit follow-ups, generate collection policies to be implemented for defaulted companies, develop default mitigation measures, and calculate unexpected and expected losses (see, for instance, Hocht et al. 2022; Muparuri and Gumbo 2022; Matenda et al. 2021c).

In practice, a myriad of studies has been devoted to default prediction. Nonetheless, most default prediction studies are restricted to publicly-owned corporates in developed nations mainly because of extensive data availability. Studies on small-to-medium enterprise (SME) default forecasting are generally limited (Karas and Reznakova 2021; Altman and Sabato 2007), and those for SME default prediction in undeveloped nations are much more restricted. In support of this, Matenda et al. (2021a) postulated that financial institutions in developing countries usually find it challenging to create formal credit evaluation procedures extensively implemented in developed countries. This is attributed to inadequate technical capacity, thin and imperfect financial markets, and deficiency of widespread infiltration by foreign and local rating corporations (see, for instance, Ozili 2019).

Although they are far from complete, research efforts by practitioners and academics toward SME default forecasting have been on the increase of late. The attention towards SME default forecasting was rekindled when the Basel II Capital Accord was introduced in 2004. The Basel II Capital Accord encourages banks to calculate their capital requirements premised on the ratings allotted to their borrowers, e.g., SMEs, by their internal rating systems (Ciampi et al. 2021). Hence, the world over, financial institutions now have SME-devoted desks and departments. In addition, given that SME loan balances contribute a significant portion of overall bank loans, SME default prediction is now examined as an explicit and independent research area in the banking industry.

To establish the quality of SME financial statements, several commercial banks are now requesting financial statements that are audited from SMEs before lending them money and even during loan payment periods. Existing literature indicated that audited and unaudited firms are characterised by different levels of default risk (Cenciarelli et al. 2018; Gul et al. 2013). In the same vein, Matenda et al. (2021b) discovered that the drivers of default probability for unaudited and audited private corporations are not the same.

This study examines the determinants of default probability for unaudited and audited SMEs under stressed conditions in Zimbabwe. There are several reasons why it is vital to analyse the determinants of SME default probability under stressed conditions in an undeveloped economy (Zimbabwe). First, SMEs are the backbone of many economies. They are an engine for stable employment, sustainable growth, and innovation (Karas and Reznakova 2021; Roy and Shaw 2021; Luo et al. 2020). Second, SMEs are dominant enterprises in developing and developed economies (Mashingaidze et al. 2021; Altman et al. 2010). World Bank Group (2022a) highlighted that SMEs comprise approximately 90% of corporates and account for more than 50% of the total employment globally. In developing countries, Njanike (2020) suggested that 99% of corporations are SMEs and the World Bank Group (2022a) articulated that formal SMEs are responsible for at most 40% of the gross domestic product (GDP). SMEs account for 50% of the GDP (Makiwa and Steyn 2019), are responsible for around 60% to 80% of total employment (Majukwa 2019), and contribute roughly 94% of the population of the corporates (Sibanda 2016) in Zimbabwe. Nonetheless, despite the economic significance of SMEs, they are associated with elevated mortality rates.

Third, SMEs are different from huge firms, e.g., they are riskier, and their financial statements are more volatile (Roy and Shaw 2021; Luo et al. 2020). Therefore, the accuracy rates of default forecasting models designed using large firm samples are relatively low when implemented in SMEs (Ciampi 2015). Fourth, Ashraf et al. (2019) and Rylov et al. (2016) indicated that implementing models created for developed markets in developing markets does not result in the provision of suitable credit. The reasons include the fact that the economic configurations of these nations are meaningfully not identical (Rylov et al. 2016; Fedorova et al. 2013) and that developed countries have more vibrant bankruptcy legislation than developing countries (Waqas and Md-Rus 2018). Fifth, extant literature has indicated that each nation has its distinctive characteristics, and therefore, techniques created for specific nations outclass universal techniques (Altman 2018; Takahashi et al. 2018).

Sixth, since SME securities are not transacted on stock exchanges, pooling default information and data for SMEs is a tricky assignment. Consequently, there is a lack of SME default data and information. This implies that borrower SME records and financial statements from financial institutions like commercial banks are paramount when examining SME default risk. Forecasting the default probability for SMEs is important because banks can modernize their SME loan evaluation procedures, examine the quality of SME loan portfolios, and assess the capability of accounting ratios to predict SME default probability. Further, SME default probability is implemented by banks when they develop policies that govern the supply and cost of loans to SMEs. Seventh, SMEs are associated with high default rates during stressed conditions, indicating that macroeconomic conditions influence SME default rates (Ciampi et al. 2021). When there is a financial and economic crisis, SMEs frequently go bankrupt. However, the literature concerning SME default prediction under downturn conditions is minimal.

Corporate bankruptcy prediction has a long history. Many bankruptcy forecasting models have been created (Altman 2018 and references therein) since the introduction of classical articles by Altman (1968) and Beaver (1966). These models can be categorised as market-based models (i.e., those that incorporate market variables), accounting-based models (i.e., those that consider accounting information), and mixed-models (i.e., those that consider both accounting data and market information). Hayden (2011) opined that the forecasting capability of statistical models is based on the belief that the historical connection between the determinants of default and the event of default is constant in the future. Nevertheless, the author (Hayden 2011) postulated that this relationship could change in the future, leading to a lower prediction ability of the models. Therefore, in practice, it is essential to develop new models under novel settings to augment the forecasting capability of the models.

To the authors' knowledge, no study has been conducted to separately examine the determinants of default probability for unaudited and audited SMEs. Further, even though SMEs are economically significant in Zimbabwe, a forecasting framework premised on a constant quantity of diverse covariates that can be implemented to predict default probability for SMEs under stressed conditions is not yet available. Therefore, this study contributes to the extant literature by analysing the determinants of default probability for unaudited and audited SMEs under stressed conditions in Zimbabwe, which is a developing country. The added value of this research paper lies in the provision of answers to the following questions:

(i) What are the significant determinants of audited and unaudited SME default probability under stressed conditions in Zimbabwe?
(ii) Are the drivers of audited and unaudited SME default probability under stressed conditions in Zimbabwe different?
(iii) Does the incorporation of macroeconomic variables results in improved classification rates for the designed SME default models?
(iv) How well do the developed models perform in classifying defaulted and non-defaulted SMEs?

Therefore, our study provides novel empirical evidence concerning the default probability drivers for unaudited and audited SMEs in a developing country (Zimbabwe) under downturn conditions.

Zimbabwe is an ideal testing ground for assessing SME default risk under stressed conditions. SMEs mold the country's economic structure, and the country has witnessed brutal and lengthy stressed economic and financial conditions over the last twenty years that have caused considerable deindustrialization and informalization of the economy (Matenda et al. 2021a, 2021b). After its total collapse, the Zimbabwean dollar was phased out in 2009 in order to stabilize the real economy, and then a bucket of foreign currencies comprising the South African rand, the euro, the British pound, the Botswanan pula, and the United States (US) dollar was adopted. Nonetheless, the US dollar materialized as corporations' functional and presentation currency (Matenda et al. 2021a, 2021b). Masiyandima et al. (2018) propounded that the materialization of the US dollar as the focal currency gave rise to negative and low inflation rates, destructively affecting the nation's growth. For instance, from October 2014 to January 2017, the country observed 28 uninterrupted months of deflation (Masiyandima et al. 2018). The World Bank Group (2022b) showed that the rate of growth of the real GDP plummeted from more than 10% per year for the years 2010–2012 to 2% in 2013, rising to 2.4% in 2014, falling to 1.8% in 2015 to 0.7% in 2016 before improving to 4.7% in 2017 and weakening to 3.5% in 2018. The government's expansionary fiscal posture resulted in the private sector's low borrowing capacity, thereby hindering private investment and growth. Additionally, for the past two decades, Zimbabwe has been experiencing chronic liquidity challenges. This negatively impacted the SME financing level of commercial banks. Deprived of access to finance, SME default rates increased. The failure rate of SMEs in Zimbabwe is one of the most terrible in the world. The stressed macroeconomic conditions experienced in Zimbabwe are not often present in advanced and developing countries.

The Reserve Bank of Zimbabwe is at the apex of the banking sector, predominated by commercial banks regarding total loans and advances, total assets, and total deposits (Reserve Bank of Zimbabwe 2018). As of 31 December 2018, the Reserve Bank of Zimbabwe (2018) stated that commercial banks accounted for 84.44% of total deposits, 83.74% of total assets, and 68.71% of total loans. Not surprisingly, SME loans constitute a substantial percentage of the total bank loans since only a restricted portion of huge yester-year firms still function in the economy. This indicates that SMEs play an essential role in the very survival of Zimbabwean commercial banks. The ownership of commercial banks in Zimbabwe stretches among the government, foreigners, indigenous persons, and corporations (Matenda et al. 2021a). In addition, Zimbabwe is yet to implement the Basel II rules entirely. The implementation of the Basel II principles is being derailed by the distressed financial and economic conditions witnessed in the country and insufficient technical capacity.

The remaining part of the article is arranged as follows: Section 2 is devoted to the review of literature review, and Section 3 describes the data and methodology. Section 4 is dedicated to empirical results and analysis. Lastly, Section 5 concludes the article and outlines opportunities for future research.

2. Literature Review

SMEs are associated with multiple challenges that threaten their survival. These challenges include increasing costs, globalisation, economic uncertainty, retaining and enticing workers, competition, compliance with rules, and moving with novel technology. Nevertheless, due to their economic significance, banks cannot overlook them since they want to enlarge their credit market shares. In practice, SME loans contribute a significant proportion of the total bank loans. Hence, it is the duty of the banks to implement robust SME default risk models when making credit decisions and computing capital requirements. Several types of default risk models have been presented in the existing literature (Matenda et al. 2021b; Altman 2018). These model types include logit models, probit models, hazard models, artificial neural networks, and machine learning techniques, among others.

Various default risk drivers are implemented when designing corporate default models. Historical financial ratios are the most commonly adopted determinants of default risk for corporate loans and bonds. However, Beaver (1966) propounded that financial ratio-premised techniques are inadequate for forecasting bankruptcy. In the same vein, Wang et al. (2011) postulated that these models depend on regularly infringed assumptions. This indicates that different types of determinants need to be incorporated when building corporate default models. Interestingly, Basel II principles encourage the inclusion of qualitative and quantitative variables in credit assessment in order to augment the predictive ability of the designed models. Consequently, financial institutions are striving to implement qualitative and quantitative determinants in credit scoring since the presentation of Basel II guidelines (Roy and Shaw 2021).

Ciampi et al. (2021) propounded that the continuous existence of substantial classification errors in the forecasting methodologies suggested in the extant literature highpoints the dire requirement to raise the kinds of covariates to be used and to examine a greater quantity of non-financial, qualitative covariates. Over the years, the simultaneous implementation of non-traditional quantitative techniques and non-financial forecasting covariates has permitted enhancements in the forecasting precision of SME techniques (Ciampi and Gordini 2013). In support of this, Gabbi et al. (2020) indicated the imperative influence of qualitative covariates in assessing credit risk for micro to medium enterprises.

High SME default rates characterise economic downturns (Ciampi et al. 2021). This indicates that the default rates for SMEs are affected by macroeconomic factors. Not surprisingly, International Financial Reporting Standard 9: Financial Instruments and Basel II/III encourage financial institutions to create default prediction models under downturn conditions (Nehrebecka 2021; International Accounting Standards Board 2014; Basel Committee on Banking Supervision 2011, 2006). Of late, academics and practitioners have been seeking models that give precedence to the high predictive ability by incorporating macroeconomic variables when predicting SME default. Matenda et al. (2021a, 2021b), Charalambakis and Garrett (2019), and Bellotti and Crook (2013) propounded that the incorporation of macroeconomic variables in default techniques augments their predictive ability.

SMEs play a crucial role in the very survival of banks since their loans contribute a large chunk of the total bank loans. To precisely assess the default risk of SME borrowers, commercial banks have been requesting financial statements that are audited from SMEs before lending them money and even during the payment periods. Audited financial statements allow financial institutions to accurately establish the quality of SME financial statements because they show the accurate financial position of the firm. European Federation of Accountants and Auditors for SMEs (2019) stated that an audit assesses the accounting records and systems, enhances the internal controls, and offers a guarantee to outside finance providers of SMEs, and an auditor offers beneficial guidance to SME management. Extant literature also indicated that audited financial statements help corporates receive funding from banks and investors since they give comfort and certainty that the finance providers would receive returns on their investments and give a guarantee that borrower firms will repay their loans. Further, Matenda et al. (2021b) postulated that investors are confident that firms audited by big corporations are associated with less risky and plausible earnings. This shows that an audit is associated with several advantages on top of the main aim of the audit of giving assurance on published accounting records. So, in practice, the demand for SME audits continues to rise. However, the verdict to have SME financial statements audited is based on the individual situations of the reporting SMEs since there are no statutory audit demands for SME financial statements.

Corporates that submit audited financial statements to the finance providers are associated with a reduced debt cost versus firms that do not (Huq et al. 2018; Cassar 2011; Minnis 2011). Matenda et al. (2021b) proffered that debt cost is positively correlated with the default probability attached to a particular obligor; therefore, the smaller the debt cost, the smaller the default probability, and the greater the debt cost, the higher the default probability. Under the same line of reasoning, Cenciarelli et al. (2018) and Gul et al. (2013) proposed that firms that possess financial statements that are audited are associated with a smaller default probability than firms with unaudited financial statements. This implies that the drivers of default probability for unaudited and audited corporates are dissimilar (see Matenda et al. 2021b).

3. Data and Methodology

3.1. Data and Variables

The main aim of this study is to separately detect and explain the determinants of default probability for unaudited and audited SMEs under stressed conditions in Zim-babwe. To achieve this, we implement two sample datasets for defaulted and non-defaulted unaudited and audited SME loan accounts retrieved from a synonymous major Zimbabwean commercial bank over the observation episode 2010–2018. We define account default as a state when an SME obligor is not expected to pay its credit commitments or is more than 90 days past due on any considerable credit commitments (Basel Committee on Banking Supervision 2006). Dataset A (preliminary) contains 110 observed non-defaulted and defaulted audited SME loan accounts, while dataset B (preliminary) consists of 107 observed non-defaulted and defaulted unaudited SME loan accounts.

To eliminate general errors in our datasets, we clean them. In this paper, we adopt an SME definition articulated in the Zimbabwean Small and Medium Enterprises Act (Chapter 24: 12). This definition considers the quantity of permanent employees, assets' value exclusive of the value of fixed assets, and yearly turnover (see Table 1).

Table 1. SME definition according to the Small and Medium Enterprises Act (Chapter 24: 12).

	Number of Permanent Employees	Yearly Turnover	Assets' Value Exclusive of the Value of Fixed Assets
Micro	1–5	US$30,000 (except for those in mining and quarrying, construction, and energy–US$50,000)	US$10,000 (exclusive of those in mining and quarrying, and construction–US$50,000, and manufacturing–US$30,000)
Small	6–30 (apart from those in construction, mining and quarrying, manufacturing, and transport with up to 40)	US$500,000 (excluding those in construction–US$1,000,000, and mining and quarrying–US$1,500,000)	US$250,000 (apart from those in manufacturing–US$500,000, and mining and quarrying, construction, and energy–US$1,000,000)
Medium	31–75	US$1,000,000 (excluding those in construction–US$2,000,000, and mining and quarrying–US$3,000,000)	US$500,000 (not including those in manufacturing–US$1,000,000, and mining and quarrying, construction, and energy–US$2,000,000)

We eliminate financial institutions, SMEs that do not meet the adopted SME definition, public institutions, and multinational corporates from our samples due to their financial statements' particularity and non-replication of the representative features of the typical Zimbabwean SMEs. We observe and track annually the loan accounts of all SMEs included in this article. All SMEs included in this study have at least one year of financial statement data. Further, we eliminate observations logged more than once, financial statements for time horizons of less than 12 months, and SMEs whose audit status is unknown from the samples. The assumption here is that the adopted financial statements offer an exact picture of the enterprises' financial situation. After data cleaning, the resulting final dataset A contains 107 audited SMEs (i.e., 84 non-defaulted and 23 defaulted SMEs) and the resulting dataset B comprises 103 unaudited SMEs (31 defaulted and 72 non-defaulted SMEs). We may conclude that unaudited SMEs are associated with a higher rate of defaulted SMEs (30.10%) than audited SMEs (21.50%). This observation supports the proposition that unaudited firms are characterized by higher default risk than audited SMEs.

Covariates that are pertinent to the analysis, widely implemented in existing studies, and that are associated with high forecasting ability in empirical studies are adopted in this article. We use twenty accounting ratios (Table 2), six loan and firm features (Table 3), and six macroeconomic factors (Table 4) to predict SME default and identify the most significant determinants of SME default risk. In this paper, we calculate the accounting ratios for defaulted SMEs using the last financial statements deposited 12 months before default. Further, we compute accounting ratios for non-defaulted SMEs using their newest financial statements deposited. Loan and firm characteristics are pooled at the loan application time. Macroeconomic variables are gathered from the World Bank Group. A priori signs for the covariates are also reflected in Tables 2–4. A positive (+) sign means that if the covariate's value surges up, the default probability rolls up. On the contrary, a negative (−) sign shows that if the determinant's value rolls up, the default probability drops.

This paper incorporates accounting ratios for leverage growth, size, activity, turnover, productivity, leverage, profitability, liquidity, and growth areas of a firm's profile. These accounting ratios represent imperative drivers of SME default risk because they disclose various financial features of a firm. Aside from the total assets' book value, the rest of the accounting ratios measure the association between two or more elements of the financial statements. This allows us to analyze the firm's performance and expose indications of financial trouble. Moreover, this study embraces dynamic ratios which connect present and historical values of particular balance sheet components, i.e., the ratios of NS/NSLY and TL/TLLY. Dynamic ratios are essential in estimating the company's default probability (Hayden 2011), since they provide new perceptions on the impact of accounting ratios when predicting default. The selected accounting ratios are widely used and are associated with superior forecasting ability in the existing literature and are appropriate to the study.

Table 2. Accounting ratios.

Accounting Ratio	Acronym	Risk Factor	A Priori Sign
Earnings before interest and tax/total assets	EBIT/TA	Profitability	−
Ordinary business income/total assets	OBI/TA	Profitability	−
Earnings before interest and tax/equity	EBIT/EQ	Profitability	−
Total liabilities/total assets	TL/TA	Leverage	+
Equity/total assets	EQ/TA	Leverage	−
Bank debt/total assets	BD/TA	Leverage	+
Short-term debt/total assets	SD/TA	Leverage	+
Earnings before interest and tax/total liabilities	EBIT/TL	Leverage	−
Current liabilities/total assets	CL/TA	Leverage	+
Total liabilities/equity	TL/EQ	Leverage	+
Total liabilities/total liabilities last year	TL/TLLY	Leverage growth	+
Accounts receivable/net sales	AR/NS	Activity	+
Accounts payable/net sales	AP/NS	Activity	+
(Current assets–current liabilities)/total assets	(CA-CL)/TA	Liquidity	−
Current assets/total assets	CA/TA	Liquidity	−
Currents assets/current liabilities	CA/CL	Liquidity	−
(Net sales–material costs)/personnel costs	(NS-MC)/PC	Productivity	−
Net sales/total assets	NS/TA	Turnover	−
Total assets	TA	Size	−
Net sales/net sales last year	NS/NSLY	Growth	−/+

Source: Matenda et al. (2021a).

Table 3. Firm and loan features.

Feature	Acronym	A Priori Sign
Loan amount	LN	+
Loan maturity period	LMP	+
Collateral value	CTV	−
Interest rate	INT	+
Age of the firm	AG	−
Time with the bank	TwB	−

Source: Matenda et al. (2021a).

Table 4. Macroeconomic variables.

Variable	Acronym	A Priori Sign
Gross national income per capita growth	GNIC	−
Unemployment rate	UR	+
Real GDP growth rate	RGDP	−
Budget balance (% GDP)	BB	+
Inflation rate (% yearly average)	INF	+
Public debt (% GDP)	PDE	+

Source: Matenda et al. (2021a).

The utilization of records and financial statements extracted from the bank allows us to use qualitative variables. The available literature indicated that incorporating soft information enhances the estimating power of corporate default techniques. Qualitative variables outlined in Table 3 are defined below:

Loan amount: Sum of money an SME borrows at the loan application time and is narrated in the loan contract. In this study, we consider commercial bank loans given to SMEs and disregard overdrafts, lines of credit, and mortgage loans.

Firm age: Age of an SME in years since its incorporation.

Collateral value: Total fair market value of assets used by an SME to receive a loan. Collateral types include machinery, residential real estate, land, and commercial real estate. Cash, inventory, blanket liens, invoices, and personal guarantees are excluded.

Interest rate: Contractual rate of interest, which is the specific rate of interest incorporated into the loan terms.

Time with the bank: Duration in years an SME has been in a relationship with the bank as its creditor.

Loan maturity period: Period (in years) from the date of loan issue until the due date for the last repayment stated in the loan contract.

Macroeconomic variables reflect macroeconomic conditions. We adopt macroeconomic variables outlined in Table 4 to reflect the downturn conditions witnessed in the Zimbabwean economy.

Observations adopted in this paper are limited. Therefore, we cannot eliminate observations with missing values because removing them could reduce the already limited datasets, thereby introducing some bias, increasing the likelihood of overlooking some valuable information for examination, and leading to an unacceptable analysis of default risk (Zhang 2016; Masconi et al. 2015; Nakagawa and Freckleton 2008; Demissie et al. 2003). Nevertheless, we cannot implement datasets with missing data for some reasons, including the following. Kang (2013) propounded that missing data may diminish the study's statistical power and generate biased forecasts, resulting in invalid conclusions. Consequently, to boost the precision of the created models and condense bias, we impute the missing data (Matenda et al. 2021a, 2021b). We implement median imputation. This technique involves the determination of the median value for the non-missing data for every covariate associated with missing data and then substituting every missing value with the estimated median value. Khan and Hoque (2020), Salgado et al. (2016), and Zhang (2016) showed that median imputation is simple (it is associated with less computational cost) and swift to execute, and it functions well with tiny numerical datasets. Median imputation is also robust when using a dataset with outliers, and it diminishes the bias related to adopting a non-representative sample (Salgado et al. 2016).

Concerning dataset A, the ratio of EQ/TA is missing 0.93% of its values, i.e., 0.93% of SMEs have missing values. We observe that only defaulted audited SMEs are associated with missing values, i.e., 4.35% of defaulted audited SMEs. Regarding dataset B, the ratio of AR/NS and the firm age are missing 0.97% of their data apiece, indicating that 1.94% of SMEs have missing data. We discover that only defaulted unaudited SMEs are associated with missing values, i.e., 6.45% of defaulted unaudited SMEs. Therefore, we can conclude that missing values are more widespread in (i) defaulted SMEs than non-defaulted SMEs in both datasets and (ii) unaudited SMEs than in audited SMEs. Outliers amplify the error variance and diminish the power of statistical tests, may cause bias, and may influence estimates. So, we winsorize outliers at the 1st and 99th centiles of the distribution instead of eliminating them. Descriptive statistics for the variables for the two sample datasets are presented. Some of the drivers are highly correlated. Given two highly correlated covariates, we eliminate one of them to address the issue of multicollinearity.

3.2. Methodology

This study adopts a binary stepwise logistic regression model to separately examine the determinants of default probability for defaulted and non-defaulted audited and unaudited SMEs. The logistic function is given by

$$\text{Logit Score} = P_i\,(y) = 1/\left(1 + e^{-z_i}\right) \quad (1)$$

where for the ith loan, z_i is the response variable given a specific set of drivers. Conceptually, z_i is described by

$$z_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_k x_{ki} + \varepsilon_i \quad (2)$$

where β_0 denotes the constant, β_1, β_2, ... , β_k signify regression coefficients, x_1, ... , x_k represent k drivers (i.e., loan and firm features, accounting ratios, and macroeconomic variables), and ε_i is the error term. This paper incorporates macroeconomic variables and accounting ratios with a time lag of one year.

We implement the whole datasets to fit the stepwise logit models for audited and unaudited SMEs due to the restricted sizes of the datasets. The limited size of the datasets forces us to disregard the split-sample approach, where the sample is divided into exploratory and confirmation samples since it could introduce some form of bias (see Xu and Goodacre 2018). This analysis implements a stepwise technique with a forward approach at a 90% confidence level to select the statistically significant covariates of SME default probability. To make sure that we include all covariates that forecast the SME default probability, we set the Alpha-to-Enter significance level (a level of significance for determining when a driver enters into a stepwise model) at 0.15 and the Alpha-to-Remove level of significance (a level of significance for determining when to eliminate a driver from a stepwise model) at 0.20. Hosmer and Lemeshow (2000) postulated that the Alpha-to-Enter level of significance of 0.15 and the Alpha-to-Remove level of significance of 0.20 incorporate all determinants that predict the outcome variable.

In this paper, we design four stepwise logistic regression models based on various amalgamations of accounting ratios, macroeconomic factors, and loan and firm features:

1. Model I: We create Model I based on accounting ratios and firm and loan features in order to predict default probability for audited SMEs.
2. Model II: We design Model II based on accounting ratios, firm and loan characteristics, and macroeconomic variables to predict the default probability for audited SMEs.
3. Model III: We develop Model III using accounting ratios and loan and firm features in order to forecast unaudited SME probability of default.
4. Model IV: We build Model IV premised on accounting ratios, macroeconomic factors, and loan and firm characteristics to predict unaudited SME default probability.

We use a 2 × 2 confusion matrix to summarize the performance of the created models (see Table 5). It reveals what the designed models are doing right and what kinds of errors they are producing. The confusion matrix indicates the below classes:

Table 5. The 2 × 2 confusion matrix.

	Predicted Observations	
	Negative	**Positive**
Actual observations		
Negative	TN	FP
Positive	FN	TP

True positive (TP): For defaulted SMEs accurately forecasted as defaulted.
False-positive (FP): For non-defaulted SMEs erroneously forecasted as defaulted.
True negative (TN): For non-defaulted SMEs rightly forecasted as non-defaulted.
False-negative (FN): For defaulted SMEs wrongly forecasted as non-defaulted.

We assess model performance by implementing in-sample classification accuracy and Type I and II error rates which are given by:

$$\text{Classification accuracy} = \frac{\text{TP} + \text{TN}}{\text{TN} + \text{FN} + \text{FP} + \text{TP}}, \tag{3}$$

$$\text{Type I error rate} = \frac{\text{FP}}{\text{TN} + \text{FP}}, \tag{4}$$

$$\text{Type II error rate} = \frac{\text{FN}}{\text{TP} + \text{FN}}. \tag{5}$$

Type I and II error rates and classification rates are used to select optimum cut-off points for the built models. We compute the classification rates and Type I and II error rates for all four models for all cut-off points 0.1–0.9 at a 10% level of significance. In this paper, as in Matenda et al. (2021a, 2021b), we select cut-off points associated with the minimal aggregate of Type 1 and II error rates and high classification rate as optimum cut-off points. We use the omnibus test, pseudo R^2 measures (Cox and Snell R^2 and Nagelkerke R^2), and Hosmer-Lemeshow (H-L) tests to assess the goodness of fit of the constructed models.

4. Empirical Results and Analysis

Table A1 indicates the descriptive statistics for the audited SME sample and Table A2 presents descriptive statistics for the unaudited SME sample used in this article. These descriptive statistics indicate the essential characteristics of the accounting ratios, firm and loan features, and macroeconomic variables adopted in the study. Tables A1 and A2 report the minimum, maximum, mean, and standard deviation values for the variables. These statistics are in harmony with those presented in other studies. For brevity reasons, Tables A3 and A4 indicate only the correlation coefficients between the determinants incorporated into the created models for audited and unaudited SMEs. Some of the determinants are highly correlated. In the analysis of dataset A, we observe that the CA/TA ratio is highly correlated with the CL/TA ratio, and the GNIC is greatly correlated with the inflation rate and the real GDP growth rate. Hence, we exclude the GNIC and CL/TA ratios from the analysis since, comparatively, they are not widely used in the existing literature. Examining dataset B, we discover that the ratio of CL/TA is highly correlated with the TL/TA ratio, and the GNIC is greatly correlated with the real GDP growth rate and the inflation rate. Consequently, we drop the CL/TA ratio and the GNIC from the analysis. We adopt the ratio of TL/TA since it takes into account total liabilities and eliminates GNIC because it is not widely used in the extant literature. Considering Tables A3 and A4 (correlation coefficient matrices for determinants incorporated into the designed models), we can say that the created logistic regression models are not affected by multicollinearity. Further, in logistic regression, a linear association between the independent and dependent variables is not needed, the distribution of error terms do not require to be normal, homoscedasticity is not needed, and the dependent variable in logistic regression is not measured on a ratio or interval scale.

In order to identify the optimum cut-off point for each designed model, we compute the classification and Type I and II error rates for the four models for all cut-off points 0.1–0.9 at a 10% level of significance (see Table 6).

Table 6. Model I-IV Type I and II error rates, classification rates, and cut-off points.

Cut-Off Point	Classification Rate	Type I Error Rate	Type II Error Rate
Model I			
0.1	53.30	57.14	08.70
0.2	74.80	27.38	17.39
0.3	84.10	11.90	30.34
0.4	83.20	07.14	52.17
0.5	84.10	03.57	60.87
0.6	80.40	02.38	82.61
0.7	81.30	01.19	82.61
0.8	79.40	01.19	91.30
0.9	79.40	0.00	95.65
Model II			
0.1	52.30	57.14	13.04
0.2	72.00	30.95	17.39
0.3	85.00	13.10	21.74
0.4	80.40	09.52	56.52
0.5	80.40	04.76	73.91
0.6	81.30	02.38	78.26
0.7	81.30	00.00	86.96
0.8	79.40	00.00	95.65
0.9	78.50	00.00	100.00
Model III			
0.1	86.40	19.44	0.00
0.2	86.40	19.44	0.00
0.3	87.40	12.50	12.90
0.4	92.20	0.56	12.90
0.5	88.30	0.56	25.81
0.6	88.30	0.56	25.81
0.7	88.30	0.56	25.81
0.8	84.50	0.56	38.71
0.9	84.50	0.00	51.61
Model IV			
0.1	77.70	26.39	12.90
0.2	77.70	26.39	12.90
0.3	82.50	19.44	12.90
0.4	92.20	05.56	12.90
0.5	96.10	00.00	12.90
0.6	88.30	00.00	38.71
0.7	88.30	00.00	38.71
0.8	84.50	00.00	51.61
0.9	84.50	00.00	51.61

Model I's optimum cut-off point is 0.3 since it has the smallest sum of Type I and II error rates (42.33%) and the highest classification rate of 84.10%. Under the same line of reasoning, cut-off points of 0.3, 0.4, and 0.5 optimize Models II, III, and IV, respectively. The SME default risk drivers included in the created models at the optimum cut-off points are now discussed.

4.1. Audited SME Default Prediction Models

4.1.1. Model I

Table 7 below indicates the covariates included in Model I and their associated Wald test *p*-values. The study results display that all the determinants incorporated into Model I are meaningfully connected to the SME default likelihood, with the (CA-CL)/TA, EBIT/TA, NS/NSLY, (NS-MC)/PC ratios, and the firm's age having a negative relationship with the SME default probability, and the ratios of BD/TA, SD/TA, and AR/NS having a positive relationship with the SME default probability.

Table 7. Model I results showing regression coefficients.

Driver	Coeff.	Wald	Sign.
(CA-CL)/TA	−2.171	5.152	0.023
EBIT/TA	−1.295	30.296	0.000
AG	−0.601	5.034	0.025
BD/TA	+2.215	5.285	0.022
SD/TA	+0.308	5.301	0.021
NS/NSLY	−0.965	10.844	0.001
(NS-MC)/PC	−0.415	4.128	0.042
AR/NS	+0.264	5.147	0.023
Constant	+0.143	4.479	0.034

Liquidity has a meaningful adverse relationship with the SME probability of default. The (CA-CL)/TA ratio, a measure of liquidity, appears in Model I with a negative regression coefficient. The implication here is that as the (CA-CL)/TA ratio rolls up, the SME default probability falls, and as the ratio of (CA-CL)/TA falls, the SME default probability rises. This is not surprising since illiquid SMEs cannot satisfy their immediate short-term payment commitments and high levels of liquidity shield SMEs against unforeseen revenue shortfalls and increases in expenses. Without enough liquidity, even viable SMEs end up defaulting on their loans. The Zimbabwean SMEs have been facing continual liquidity pressures, particularly against a background of illiquid financial markets and the absence of government support. The establishment of the multi-currency system in 2009 and the resultant surfacing of the US dollar as the principal currency instigated the national liquidity crisis that has been troubling SMEs for so long. Moreover, given that Zimbabwean SMEs are regarded as risky enterprises and their history of not reimbursing loans due to their privileged culture that originated from receiving free government funds, financial institutions, primarily commercial banks, were and are still reluctant to lend to SMEs. The observed negative association between liquidity and corporate default agrees with the findings of Matenda et al. (2021a, 2021b) for Zimbabwean private firms, Jensen et al. (2017) for Danish private corporates, Altman et al. (2010) for United Kingdom SMEs, and Altman and Sabato (2007) for US SMEs. Bauer and Edresz (2016) found a negative association between bankruptcy probability for Hungarian firms and liquidity. Durica et al. (2019) uncovered an adverse relationship between the business failure of corporates operating in V4 countries and liquidity.

As expected, the EBIT/TA ratio, a profitability measure, is linked with a negative sign, signifying that if the ratio surges up, the SME default probability drops, and if the ratio falls, the SME default probability surges up. The implication is that less profitable SMEs are exposed to a higher probability of default than more profitable SMEs. Significantly profitable SMEs can fund their working capital requirements, raise funds from financial institutions, and attract investors. Profitable corporates can reimburse their loans, thus dropping their probability of default. In practice, lenders, before they grant loans, examine the profitability levels of borrowers to determine their repayment capacity. In Zimbabwe, several SMEs are cash flow positive but are not profitable, adversely affecting their capacity to receive commercial loans from banks, thereby increasing their default rates. Matenda et al. (2021a) uncovered a negative association between profitability and private firm default likelihood in a developing country, Zimbabwe, and Jensen et al. (2017) discovered an adverse connection between profitability and default probability for Danish private firms. In addition, the findings of Bauer and Edresz (2016), Charalambakis (2014, 2015), Hayden (2011), Ohlson (1980), and Shumway (2001) are also consistent with our discovery of a negative correlation between profitability and corporate default.

Our results indicate that the firm age appears in Model I with a negative coefficient, showing that as the firm age rises, the SME probability of default falls, and as the firm age drops, the SME default probability rises. That is to say, younger SMEs are more likely to default than mature SMEs. Matenda et al. (2021a) postulated that, in Zimbabwe, young corporations are associated with drastic internal shortcomings, and they battle more with stressed situations and severer levels of competition. Young firms usually do not profit from economies of scale, have limited operating experience, have limited bargaining power when negotiating with financial institutions and suppliers, and typically operate in small markets. Additionally, young SMEs' future cash flows and their timing are characterized by high uncertainty levels. Moreover, young SMEs have a restricted number of clients and suppliers and lack market and product diversification. Our discovery of the negative correlation between firm age and default probability is consistent with the findings of Ciampi et al. (2021), Abdullah et al. (2019), Kenney et al. (2016), and Bandyopadhyay (2006). On the other hand, Switzer et al. (2018) and Luppi et al. (2007) proffered that the firm's age and the default likelihood are positively related.

Although we do not anticipate a negative or positive coefficient of regression for the NS/NSLY ratio, our results show that the regression coefficient for the ratio of NS/NSLY is negative. This indicates that as the NS/NSLY ratio rolls up, the SME default probability cascades, and as the ratio of NS/NSLY decreases, the SME default probability rolls up. In reality, a corporation should grow up as an alternative to scaling down (Matenda et al. 2021b). In Zimbabwe, among other things, growing SMEs reap the benefits of economies of scale and can receive credit from financial institutions since growth is seen as a sign of financial viability. Furthermore, growing firms can withstand external shocks such as those emanating from technology or market changes and competition, make more profits and sales, invest more in their businesses, reach new clients, and penetrate new markets. Generally, growth is regarded as an antecedent to achieving acceptable profitability and competitive advantages (Markman and Gartner 2002). MacMillan and Day (1987) proposed that swift growth can result in greater profitability. Bauer and Edresz (2016) postulated that the growth of sales and the bankruptcy probability for Hungarian firms are negatively correlated. Not in agreement with our discovery, Matenda et al. (2021a) uncovered a positive association between the NS/NSLY ratio and the default probability for private firms. Hayden (2011) revealed a positive connection between the ratio of NS/NSLY and the Austrian corporates' default probability.

As we expect in this analysis, the regression coefficient for the ratio of (NS-MC)/PC is negative, signifying that as the driver surges up, the SME probability of default drops, and as the ratio falls, the SME default probability rolls up. The (NS-MC)/PC ratio is a measure of productivity. Corporate productivity is an imperative driver of a corporation's bankruptcy probability (Aleksanyan and Huiban 2016). The authors (Aleksanyan and Huiban 2016) further stated that productivity is associated with a beneficial influence on reducing bankruptcy risk. The Zimbabwean SMEs associated with high productivity levels are feasible, effective, and efficient enough to wilt the influence of external shocks that may push SMEs into default. Bottazzi et al. (2008) highlighted that high levels of SME productivity could result in low operational costs, high profitability, and optimization of resources and that they can subject SMEs to several growth opportunities. Moreover, Blanchard et al. (2012) indicated that productivity is associated with a considerable adverse effect on the corporate's likelihood of exit, and Bellone et al. (2006) propounded that the nearer the corporations are to the time of exit, the lesser the level of productivity. Farinas and Ruano (2005) indicated that higher productivity reduces corporates' probability of exit. Dwyer (1998) revealed that corporates at the productivity distribution's lowest level are associated with the most significant rates of exit, and Baily et al. (1992) opined that the corporate likelihood of death is elevated amongst corporates associated with low-level productivity. In the existing literature, Matenda et al. (2021a, 2021b) and Hayden (2011) are some of the sources that propounded that there is an adverse association between the (NS-MC)/PC ratio and the firm default probability.

The generated results indicate that leverage measures, i.e., the ratios of BD/TA and SD/TA, appear in Model I with positive regression coefficients, indicating that as the ratios increase, the SME default probability rolls up, and as the ratios fall, the SME default probability drops. Zimbabwean corporates are often undercapitalized (see, for instance, Matenda et al. 2021a), and they use debt finance to fund their investment and working capital needs. Consequently, the majority of them are highly leveraged. Too much debt for SMEs decreases their profitability levels and increases their default probability. Loan reimbursements are a crippling expense to Zimbabwean SMEs since they borrow funds for investments associated with long-term returns. As a result, they start reimbursing those loans before they start receiving returns. In addition, regular repayment of loans denotes that a smaller proportion of their revenue goes to financing operations and investments, which have devastating consequences (see Matenda et al. 2021a). Further, banks are reluctant to provide more funding to already highly leveraged SMEs. If a highly leveraged SME manages to secure a loan, the rate of interest will be high enough to account for that increased risk, which increases the default probability of that SME. Aleksanyan and Huiban (2016) emphasised that credit costs significantly and positively influence bankruptcy likelihood. Interestingly, it is documented that highly leveraged corporations are sensitive to distressed conditions because high debt levels decrease their cushion against adverse shocks (Falkenstein et al. 2000). Gallucci et al. (2022), Jensen et al. (2017), Brındescu-Olariu (2016), Charalambakis (2014, 2015), and Hayden (2011) are some of the authors that exposed a positive association between default likelihood and leverage.

The AR/NS ratio, an activity measure, has a positive regression coefficient, highlighting that as it upsurges, the SME default probability rises, and as it falls, the SME default probability decreases. In support of this, a positive connection between the ratio of AR/NS and the corporation probability of default is well documented for developing countries (see Matenda et al. 2021a, 2021b) and developed countries (see Hayden 2011). Zimbabwe has been witnessing a chronic liquidity crisis and credit availability has been restricted for too long. Hence, several buyers could not purchase goods using cash on delivery as a payment option (Matenda et al. 2021a, 2021b). They could buy goods on credit terms. Consequently, numerous SMEs have higher ratios of AR/NS. Amplified accounts receivable levels adversely influence firms' profitability, cash flow, and liquidity positions since they cannot be amassed timeously (see, for example, Matenda et al. 2021a). Additionally, high accounts receivable levels are associated with increased contagion risk. Contagion risk is when a debtor's default gives birth to credit losses on the creditor's part. Credit losses push SMEs into default. This shows that credit contagion has a cascading effect between suppliers and buyers in a supply chain. Bastos and Pindado (2013) propounded that, in the supply chain, in the context of a financial crisis, trade credit contagion is a common feature. Monteiro (2014) highlighted that, in a financial crisis, credit constraints encourage firms associated with amplified accounts receivable to postpone their settlements to sellers. Additionally, Forgione and Migliardo (2019) opined that the number of payables and the unanticipated postponement in the trade credit payment is firmly associated with the financial distress of corporates. The authors (Forgione and Migliardo 2019) found that corporates in financial distress broadly make use of trade credit and are negatively affected by receivables postponement.

In terms of performance, the goodness of fit measures' results indicates that Model I is a good fit for the data. The omnibus test *p*-value for Model I is smaller than 0.05; therefore, the model is statistically significant. Model I has a Cox and Snell R^2 value of 0.416 and a Nagelkerke R^2 value of 0.589. Hence, Model I elucidates between 41.60% and 58.90% of the outcome variable's variance. The *p*-value of the H-L test for Model I is greater than 5%, indicating that the observed and predicted values of the outcome variable are closely analogous.

4.1.2. Model II

Table 8 below outlines Model II results.

Table 8. Model II results showing regression coefficients.

Driver	Coeff.	Wald	Sign.
(CA-CL)/TA	−2.193	5.065	0.024
EBIT/TA	−0.573	4.501	0.034
RGDP	−1.077	6.327	0.012
INF	−0.409	4.294	0.038
TwB	−0.505	17.322	0.000
BD/TA	+1.204	6.602	0.010
CA/TA	+0.153	5.002	0.025
EBIT/TL	+0.304	6.032	0.014
AR/NS	+0.298	5.727	0.017
Constant	+0.180	5.490	0.019

Our empirical results indicate that all the covariates that makeup Model II are profoundly connected to the SME default likelihood, with the ratios of (CA-CL)/TA and EBIT/TA, the real GDP growth rate, the time with the bank and the rate of inflation having an adverse association with the SME default likelihood, and the BD/TA, CA/TA, EBIT/TL, and AR/NS ratios positively related to the SME default likelihood. The signs for the regression coefficients for the ratios of (CA-CL)/TA, EBIT/TA, BD/TA, and AR/NS are similar to those in Model I.

In this current study, we discover a negative correlation between SME default probability and the real GDP rate of growth. As the growth rate of the real GDP increases, the SME default probability drops, and as the real GDP growth rate falls, the default probability for SMEs rolls up. This is not astonishing because the rate of growth of the real GDP measures economic growth. It confirms whether the country is growing from one year to another or not, i.e., it indicates the economy's general health. Therefore, an upsurge in the real GDP rate of growth indicates that the country is doing well. The implication of this finding is that SMEs are sensitive to business cycles. Extant literature indicated that default is more likely when the economy is not doing good or in recessions since it is challenging for borrowers to repay their debt during these times. The negative correlation between default probability and the real GDP rate of growth agrees with the findings of Matenda et al. (2021a, 2021b) and Jakubik and Schmieder (2008).

Our results indicate that the rate of inflation has a negative regression coefficient, signifying that as the rate of inflation upsurges, the SME default probability cascades, and as the inflation rate drops, the SME default probability surges up. Inflation favours and benefits the borrowers since it allows borrowers to reimburse creditors with money that is worth less than it was when it was initially borrowed. Even though borrowers repay the same amount of money they borrowed, in real terms, they pay less. Consequently, the debt burden is reduced, and borrowers benefit. Further, the episode under observation is associated with a period of deflation (see Masiyandima et al. 2018). Deflation upsurges the real values of money and debt, making it more burdensome for borrowers to pay back the borrowed funds since they will be using stronger dollars to repay their loans (see Fleckenstein et al. 2017; Tokic 2017; Mahonde 2016; Bhamra et al. 2011). Additionally, deflation depresses expenditure, and as a result, corporations receive lower revenues, and their profits become depressed. In support of this, Matenda et al. (2021a, 2021b) uncovered an adverse rapport between the default likelihood for privately-owned corporates and the inflation rate in a developing country.

The study results show that the ratio of EBIT/TL appears in Model II with a positive sign, signifying that as it escalates, the SME default likelihood rolls up, and as it falls, the SME default likelihood drops. Our a priori sign for the EBIT/TL ratio is negative. Hence, the positive sign for the ratio of EBIT/TL is against our expectations. However, the revealed result is motivated more by TL (denominator) than EBIT (numerator). Amplified EBIT/TL ratios for the Zimbabwean SMEs originate from small values of TL as a result of cut trade credit. Murro and Peruzzi (2022) postulated that, for SMEs, trade credit is one of the vital springs of outside financing behind bank lending. Zimbabwean SMEs are generally regarded as risky enterprises. They cannot simply access credit from commercial banks. As a result, they depend more on trade credit. Nonetheless, since SMEs in Zimbabwe usually operate in financial distress, they find it hard to access trade credit to support sales. Even if enterprises manage to secure trade credit, they only enjoy it over a short-term period before the providers become credit-repressed and cut trade credit (Matenda et al. 2021a). Moreover, the suppliers have restrained access to formal credit because of chronic liquidity challenges. Thus, they are forced to reduce trade credit levels to client SMEs. Matenda et al. (2021a) proposed that trade credit restrictions shove distressed corporates into default since no alternative credit source is available to them. McGuinness et al. (2018) articulated that, in a financial crisis, trade credit positively influences the survival of financially restricted SMEs. For more expositions on the hypothesis of substitutability between bank credit and trade credit, the interested reader is referred to Casey and O'Toole (2014), Bastos and Pindado (2013), and Garcia-Appendini and Montoriol-Garriga (2013). Congruent with the findings of this study, Matenda et al. (2021a, 2021b) discovered a positive association between the ratio of EBIT/TL and private company default probability in Zimbabwe.

In this analysis, we reveal that the ratio of CA/TA, a liquidity measure, has a positive regression coefficient, signifying that the SME default probability upsurges as the CA/TA ratio rises, and as the CA/TA ratio falls, the SME default probability drops. This finding is against our intuition since the extant literature indicated that the CA/TA ratio is associated with a negative sign (see, Durica and Svabova 2019). We reveal that the unexpected positive sign related to the ratio of CA/TA is more inspired by the numerator (CA) than the denominator (TA). Numerous SMEs are loaded with accounts receivable (which they cannot gather in time) since clients prefer to use trade credit due to the critical liquidity challenges bedeviling the economy. Clients cannot procure goods on a cash basis and cannot pay in advance. Since credit contagion has a cascading effect between suppliers and buyers, SMEs loaded with vast volumes of accounts receivable eventually default on or postpone their payments to creditors. Matenda et al. (2021a, 2021b) are some sources that discovered a positive relationship between the CA/TA ratio and corporate default probability.

We discover that the time with the bank has a negative regression coefficient. This means that as the time with the bank escalates, the SME probability of default cascades, and as the time with the bank decreases, the SME default probability rises. Our discovery is supported by Matenda et al. (2021a, 2021b) and Jensen et al. (2017). SMEs with longer relationships with their banks are characterised by lower default probability than SMEs with shorter relationships with their banks. The Zimbabwean SMEs with longer relationships with their banks are in a superior position to endure distressed situations versus SMEs with shorter relationships with their banks. Under distressed conditions, SMEs with longer relationships with their banks gain from, among other things, a guarantee to obtain credit from banks, low prices for services rendered, a chance to renegotiate credit terms, and low rates of interest. Berger and Udell (1995) and Brick and Palia (2007) discovered that obligors with longer relationships are associated with lesser rates of interest and lesser collateral requirements. Further, Murro and Peruzzi (2022) proposed that corporates with close and long-term relationships with their major banks are related to suppliers' greater volumes of trade credit. In the same vein, Angelini et al. (1998) and Petersen and Rajan (1994) indicated that longer relationships augment corporates' access to credit.

Considering the values of goodness-of-fit measures, Model II is a good fit with the data. The omnibus test p-value for Model II is less than 0.05; thus, the model is statistically significant. Model II has a Cox and Snell R^2 value of 0.494 and a Nagelkerke R^2 value of 0.700. Hence, Model II elucidates between 49.40% and 70.00% of the outcome variable's variance. The p-value of the H-L test for Model II is greater than 5%, signifying that the observed and predicted values of the outcome variable are closely similar.

Comparing Cox and Snell R^2 and Nagelkerke R^2 values for Models I and II, we observe that Model II is better than Model I. Model II describes between 49.40% and 70.00% of the outcome variable's variance, while Model I explains between 41.60% and 58.90% of the outcome variable's variance. This implies that a model with accounting ratios, firm and loan characteristics, and macroeconomic variables describe SME default probability better than a model with only accounting ratios and firm and loan features. Thus, we can conclude that fusing accounting ratios and firm and loan characteristics with macroeconomic variables when designing SME default prediction models results in a better model fit, leading to considerable augmentation of the models' classification rates.

4.2. Unaudited SME Default Prediction Models

4.2.1. Model III

The results of this analysis show that all the drivers that appear in Model III (see Table 9) are substantially linked to the SME probability of default, with the ratios of (CA-CL)/TA, (NS-MC)/PC, and EBIT/TA and the time with the bank adversely related to the SME default probability, and the ratio of BD/TA, the age of the firm, the (NS-MC)/PC ratio and the interest rate positively linked to the SME default probability. We reveal that the signs for the regression coefficients for the ratios (CA-CL)/TA, BD/TA, and EBIT/TA are akin to the signs indicated in Models I and II. Further, the sign for the regression coefficient for the time with the bank is like that in Model II, and the sign for the regression coefficient for the (NS-MC)/PC ratio is analogous to that in Model I.

Table 9. Model III results showing regression coefficients.

Driver	Coeff.	Wald	Sign.
(CA-CL)/TA	−2.064	4.775	0.029
EBIT/TA	−1.104	10.965	0.001
(NS-MC)/PC	−0.771	10.830	0.001
TwB	−0.505	17.322	0.000
NS/NSLY	+1.766	9.415	0.002
BD/TA	+2.245	6.063	0.014
AG	+0.560	8.738	0.003
INT	+0.662	10.841	0.001
Constant	−2.193	5.065	0.024

Our study results indicate that firm age dynamics significantly affect the unaudited SME default profitability. The firm's age has a positive regression coefficient, showing that as age rises, the SME default probability increases, and as the age rolls down, the SME default probability drops. This goes against our expectations. However, it can be attributed to several factors. New SMEs are flexible and efficacious innovators who operate in niche markets. Under the same reasoning, Kucher et al. (2018) and Dean et al. (1998) stated that new corporates are good innovators that operate in smaller niche markets due to their superior speed and flexibility. On the other hand, Matenda et al. (2021b) postulated that "in Zimbabwe, older and mature unaudited private firms mainly fail due to lack of strategic foresight, increased competition, innovativeness inflexibility, economic slowdowns, costly organizational frameworks, high-cost pressures and a lack of adaptability." Kucher et al. (2018) articulated that SMEs that are mature wrestle more with augmented competition and economic slowdowns. Existing literature also indicated that older corporates are usually more bureaucratic as compared to newer corporates and are more expected to fail as a result of high-cost pressure stemming from unwanted organizational frameworks against a backdrop of deteriorating profit margins or falling turnover in dynamic sectors (see Amankwah-Amoah 2016; Ooghe and Prijcker 2008; Levinthal 1991). In the same vein, Lukason and Hoffman (2015) discovered that exogenous insolvency causes are considerably associated with mature firms, and Baldwin et al. (1997) suggested that exogenous circumstances (e.g., economic downturns and amplified competition) mostly push older corporates into bankruptcy. Switzer et al. (2018) and Luppi et al. (2007) revealed that the firm's age and the default probability are positively correlated, and Succurro and Mannarino (2013) proposed that the age of the firm and bankruptcy are positively correlated in developing countries. On the other hand, Matenda et al. (2021a) postulated that a firm's age is negatively related to the default likelihood of private firms.

This current analysis does not anticipate a negative or positive regression coefficient for the NS/NSLY ratio. Nonetheless, we discover that the regression coefficient for the NS/NSLY ratio is positive. The implication is that as the NS/NSLY ratio upsurges, the SME probability of default rolls up, and as the NS/NSLY ratio drops, the SME default probability falls. The positive sign for the NS/NSLY ratio is attributed to several factors. Not all growth is desirable. Fitzsimmons et al. (2005) postulated that rapidly growing corporates face challenges related to growth that result in shrunk profitability and possibly financial difficulties. Basically, rapid growth needs sustained investments (Grover G. Arti and Olafsen 2019). Wang (2016), Lee (2014) and Brush et al. (2009) opined that companies that are linked to high-growth are characterized by shortcomings in these disciplines: cash flow, skill deficiencies, sourcing finance, recruitment, management, and securing apposite premises. Notably, if growth is not funded using retained earnings, corporates need to use equity or debt finance (Falkenstein et al. 2000; Fitzsimmons et al. 2005). Given that a myriad of Zimbabwean SMEs are owned by individuals and families with restrained financial resources and are undercapitalized, their rapid growth is financed through debt, exposing them to more challenges since debt comes at a cost. A combination of lack of management skills of the owners and high leverage under stressed conditions has been pushing a multiplicity of Zimbabwean SMEs into default. Hayden (2011) found a positive connection between the ratio of NS/NSLY and company default probability for Austrian firms. On the other hand, Matenda et al. (2021b) discovered a negative association betweeen the NS/NSLY ratio and the default likelihood for audited private corporates in a developing country.

Our empirical findings show that the interest rate has a positive regression coefficient, signifying that as the interest rate upsurges, the SME default likelihood increases, and as the interest rate falls, the SME default probability drops. The rate of interest is associated with an inherent indirect cost on the advances or loans given by financial institutions, mainly commercial banks, with implications on the default of loans (Matenda et al. 2021b). Matenda et al. (2021b) further opined that high-interest rates increase the debt burden on borrowers, making it challenging and less attractive for private corporations to reimburse loans associated with high-interest rates and, eventually, shoving them into default. Aleksanyan and Huiban (2016) discovered that credit cost is associated with a significant and positive influence on bankruptcy likelihood. Michalkova et al. (2018) stated that numerous corporates fail to reimburse their bank loans because of high rates of interest. Moreover, due to the high loan interest rates, SMEs are reluctant to borrow more funds from banks. Amonoo et al. (2003) propounded that interest rates adversely influence SME loan repayment performance and revealed an adverse relationship between high-interest rates and SME credit demand. Under distressed conditions, Matenda et al. (2021b) found a positive connection between bank loan interest rates and private firm default probability. Everett and Watson (1998) postulated that the association between small business failure and the rates of interest is positive.

The omnibus test *p*-value for Model III is smaller than 0.05; thus, the model is statistically significant. Model III has a Cox and Snell R2 value of 0.485 and a Nagelkerke R2 value of 0.687. Henceforth, Model III explains between 48.50% and 68.70% of the outcome variable's variance. The *p*-value of the H-L test for Model III is greater than 5%, suggesting that the observed and predicted values of the outcome variable are closely analogous. Considering the values of these goodness-of-fit measures, Model III is a good fit with the data.

4.2.2. Model IV

The outcomes of this analysis signify that all the determinants that appear in Model IV (see Table 10) are meaningfully linked to the SME probability of default, with the ratios of (CA-CL)/TA and EBIT/TA, the real GDP rate of growth, the time with the bank and the rate of inflation having an adverse relationship with the SME default likelihood, and the BD/TA and NS/NSLY ratios, the firm's age and the interest rate having a positive correlation with the SME default likelihood. We expose that the regression coefficient signs for the (CA-CL)/TA, BD/TA, and EBIT/TA ratios are akin to those in Models I, II, and III. The coefficient sign for the time with the bank is like that in Models II and III, and the signs for regression coefficients for the NS/NSLY ratio, the interest rate, and the firm's age are analogous to those in Model III. Moreover, the coefficient signs for the inflation rate and the real GDP rate of growth are similar to those in Model II.

Table 10. Model IV results showing regression coefficients.

Driver	Coeff.	Wald	Sign.
(CA-CL)/TA	−2.407	7.618	0.006
EBIT/TA	−0.613	10.993	0.001
RGDP	−1.500	13.789	0.000
TwB	−0.530	16.576	0.000
INF	−0.767	4.314	0.038
NS/NSLY	+0.435	4.183	0.041
BD/TA	+2.511	4.081	0.043
AG	+0.298	5.727	0.017
INT	+0.304	6.032	0.014
Constant	+0.207	7.602	0.006

The omnibus test *p*-value for Model IV is smaller than 0.05; consequently, the model is statistically significant. Model IV has a Cox and Snell R^2 value of 0.545 and a Nagelkerke R^2 value of 0.773. Henceforth, Model IV explains between 54.50% and 77.30% of the outcome variable's variance. The *p*-value of the H-L test for Model IV is greater than 5%, telling that the observed and predicted values of the outcome variable are closely similar. In terms of performance, the values of the goodness of fit measures indicate that Model IV is a good fit with the data.

Model IV is better than Model III considering the Cox and Snell R^2 and Nagelkerke R^2 values for these models. Model IV describes between 54.50% and 77.30% of the outcome variable's variance, whereas Model III explains between 48.50% and 68.70% of the outcome variable's variance. This indicates that a model that incorporates macroeconomic factors in addition to accounting ratios and firm and loan features explains SME default probability better than a model that considers only accounting ratios and firm and loan characteristics. Accordingly, we can conclude that combining financial ratios and firm and loan features with macroeconomic factors when creating default prediction models for SMEs leads to better model fit, resulting in significant enhancement of the models' classification rates.

5. Conclusions

The aim of the study was to separately detect and explain the determinants of default probability for defaulted and non-defaulted unaudited and audited SMEs under stressed financial and economic conditions in a developing country (Zimbabwe). In this context, we used four stepwise logistic regression models and adopted two distinct datasets for unaudited and audited SMEs gathered from an anonymous major Zimbabwean commercial bank over the observation period 2010–2018.

In this study, we discover that the default drivers for audited and unaudited SMEs are not the same. Additionally, the study results indicate that accounting data helps differentiate defaulted SMEs from non-defaulted SMEs under stressed conditions in Zimbabwe. Further, we offer compelling evidence that SME default models incorporating loan and firm features, macroeconomic variables, and accounting ratios best describe the default likelihood for Zimbabwean unaudited and audited SMEs. SME default models with macroeconomic factors are associated with higher in-sample classification rates than SME default models without macroeconomic factors. The in-sample classification rate for an audited SME default prediction model with macroeconomic variables (Model II) is 85%, while that for the unaudited SME default forecasting model is 96.10% (Model IV). Basically, the classification rates of SME default prediction models are enhanced by amalgamating financial ratios and firm and loan features with macroeconomic factors.

Specifically, the article reveals that the (CA-CL)/TA ratio, the ratio of EBIT/TA, the real GDP rate of growth, the inflation rate, and the time with the bank have an adverse relationship with the default likelihood, and the ratios of BD/TA, CA/TA, EBIT/TL, and AR/NS have a positive relationship with the default likelihood for Zimbabwean audited SMEs. On the contrary, the analysis finds that the (CA-CL)/TA ratio, the ratio of EBIT/TA, the rate of inflation, the real GDP rate of growth, and the time with the bank have an adverse association with the default likelihood, and the ratio of NS/NSLY, the BD/TA ratio, the firm's age, and the interest rate have a positive association with the default likelihood for Zimbabwean unaudited SMEs.

We recommend financial institutions model separately the default probability for audited and unaudited SMEs. Audited and unaudited firms have different characteristics. Compared to unaudited firms, audited firms are associated with less risky and plausible earnings, reduced debt cost, low default risk, and easier access to finances. This indicates that audits are beneficial and hence, SMEs are encouraged to have their financial statements audited. Additionally, it is recommended that financial institutions should combine financial ratios and firm and loan characteristics with macroeconomic variables when designing default probability models for SMEs in order to augment their classification rates.

In practice, it is essential to forecast SMEs' default probability. Predicting SME default probability helps financial institutions in decision-making processes, credit follow-ups, and loan pricing processes, as they can determine the cost of credit. The default risk associated with SMEs concerns microprudential and macroprudential supervisors as they want to maintain stability in the banking sector and the economy at large. Without effective bank lending, the growth of SMEs is stalled substantially. Therefore, this analysis is of interest to policymakers and practitioners who help SMEs by eradicating associated credit restrictions. The outcomes of this paper can be implemented to create policies that make financing SMEs more efficient and smoother. Additionally, given the economic significance of SMEs, regulators who strive to stimulate economic growth and development are interested in the dynamics of SME probability of default. Further, the findings of this article give political and economic validation for the special assessment of default probability for unaudited and audited SMEs.

Even though this study has generated fascinating results, it has some limitations. The adopted approach for selecting optimum cut-off points for the designed models gives the same weight to Type I and II errors even though Type II errors are costlier than Type I errors. We disregard the split-sample approach and implement whole datasets to fit the stepwise logit models due to the constrained sizes of the datasets. Therefore, in practice, the results of this study need to be interpreted with caution. For future research, this study can be extended in several ways. Techniques for selecting optimum model cut-off points that do not give the same weight to Type I and II errors could be implemented. The study can be stretched by employing massive datasets with varied dimensionality and convolution gathered from various sources over a long time-period so that sample datasets can be divided into exploratory and confirmation samples. To improve the classification ability of the models, more sophisticated alternative techniques can be adopted, e.g., neural networks and support vector machines. Further, a more all-embracing basket of drivers can be employed in future research when developing SME default prediction models.

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Appendix A

Table A1. Descriptive statistics for audited SMEs.

Driver	Min.	Max.	Mean	SD
		Accounting ratios		
TL/TA	0.01	1.32	0.62	0.34
BD/TA	0.01	0.59	0.23	0.18
EQ/TA	−0.14	0.99	0.47	0.31
CA/CL	0.04	4.49	1.64	1.26
SD/TA	0.01	0.60	0.19	0.17

Table A1. *Cont.*

Driver	Min.	Max.	Mean	SD
AP/NS	0.05	4.53	0.36	0.77
AR/NS	0.03	5.01	0.88	1.58
NS/TA	0.01	9.19	1.75	2.06
(NS-MC)/PC	−1.27	11.42	3.58	3.31
OBI/TA	−0.15	1.04	0.33	0.41
EBIT/TA	−0.09	1.11	0.11	0.25
(CA-CL)/TA	−0.26	0.96	0.12	0.29
TA *	28.80	199.80	125.10	57.32
NS/NSLY	0.22	3.39	1.13	0.71
EBIT/EQ	−2.16	4.36	0.29	0.84
EBIT/TL	−1.11	2.87	0.46	0.94
TL/TLLY	0.27	2.95	1.19	0.59
TL/EQ	−3.36	3.93	1.19	1.28
CL/TA	0.01	1.21	0.44	0.30
CA/TA	0.04	0.99	0.60	0.34
		Firm and loan factors		
LN *	1.00	130.00	38.36	32.15
INT	4.00	19.00	11.83	3.61
AG	2.00	31.00	13.37	7.70
CTV*	2.50	165.82	61.24	40.49
TwB	1.00	22.00	7.98	3.71
LMP	1.00	8.00	3.29	2.12
		Macroeconomic variables		
GNIC	−1.50	20.70	3.95	6.65
INF	−2.40	10.60	0.54	3.57
UR	4.90	5.60	5.34	0.22
RGDP	0.70	19.70	4.53	5.52
PDE	37.10	54.20	43.31	6.06
BB	−11.20	−1.10	−3.12	3.30

SD represents standard deviation. * In ten-thousands of US dollars.

Table A2. Descriptive statistics for unaudited SMEs.

Driver	Min.	Max.	Mean	SD
		Accounting ratios		
TL/TA	0.04	1.41	0.73	0.35
BD/TA	0.01	0.36	0.13	0.11
EQ/TA	−0.27	0.99	0.39	0.34
CA/CL	0.15	3.90	1.20	0.92
SD/TA	0.01	0.46	0.13	0.12
AP/NS	0.04	2.74	0.45	0.58
AR/NS	0.05	5.63	0.47	1.15
NS/TA	0.01	5.39	1.40	1.42
(NS-MC)/PC	−1.78	9.92	1.19	2.22
OBI/TA	−0.56	0.30	0.02	0.24
EBIT/TA	−0.21	0.38	0.06	0.13
(CA-CL)/TA	−1.07	0.32	−0.08	0.31
TA *	28.73	197.66	103.47	60.84
NS/NSLY	0.50	5.36	3.49	2.12
EBIT/EQ	−3.78	4.69	0.36	1.09
EBIT/TL	−1.16	2.78	0.25	0.58
TL/TLLY	0.51	3.89	1.23	0.60
TL/EQ	−4.71	5.41	0.25	3.07
CL/TA	0.09	2.88	0.69	0.46
CA/TA	0.05	0.95	0.49	0.30
		Firm and loan factors		
LN *	1.80	87.00	31.32	24.67
INT	5.00	21.00	15.44	5.43
AG	1.00	24.00	7.38	5.32
CTV *	10.00	111.85	52.60	31.08
TwB	1.00	13.00	5.04	3.97
LMP	1.00	5.00	2.61	1.60
		Macroeconomic variables		
GNIC	−1.5	16.00	4.38	6.36
UR	4.90	5.60	5.41	0.22
RGDP	0.70	16.70	5.14	6.13
PDE	37.20	54.20	43.17	6.56
BB	−11.20	−1.10	−2.58	2.73
INF	−2.40	3.70	0.36	2.27

SD represents standard deviation. * In ten-thousands of US dollars.

Table A3. Correlation coefficients between determinants incorporated in Models I and II.

	BD/TA	SD/TA	AR/NS	(NS-MC)/PC	EBIT/TA	(CA-CL)/TA	EBIT/TL	CA/TA	NS/NSLY	AG	TwB	RGDP	INF
BD/TA	1.00												
SD/TA	0.31	1.00											
AR/NS	−0.02	0.00	1.00										
(NS-MC)/PC	−0.09	−0.06	−0.20	1.00									
EBIT/TA	0.24	−0.03	−0.11	−0.08	1.00								
(CA-CL)/TA	−0.07	−0.01	−0.02	0.04	0.44	1.00							
EBIT/TL	0.28	−0.06	−0.11	−0.07	0.78	0.19	1.00						
CA/TA	0.00	0.13	−0.03	0.03	0.35	0.78	0.05	1.00					
NS/NSLY	−0.05	0.02	−0.03	0.02	−0.02	−0.05	0.01	−0.06	1.00				
AG	0.04	−0.07	−0.02	0.07	0.02	−0.04	0.08	−0.03	−0.06	1.00			
TwB	−0.12	−0.01	0.00	0.02	−0.06	−0.02	−0.08	0.06	0.01	0.30	1.00		
RGDP	−0.06	−0.09	−0.09	0.02	−0.09	−0.13	−0.12	−0.05	0.03	0.10	0.02	1.00	
INF	−0.08	0.09	−0.10	0.05	−0.21	−0.13	−0.20	−0.07	0.04	0.03	0.04	0.47	1.00

Table A4. Correlation coefficients between determinants incorporated in Models III and IV.

	BD/TA	(NS-MC)/PC	EBIT/TA	NS/NSLY	(CA-CL)/TA	INT	AG	TwB	RGDP	INF
BD/TA	1.00									
(NS-MC)/PC	0.15	1.00								
EBIT/TA	−0.26	−0.06	1.00							
NS/NSLY	0.15	0.78	−0.06	1.00						
(CA-CL)/TA	−0.47	−0.01	0.42	−0.01	1.00					
INT	0.21	0.12	0.03	0.12	−0.25	1.00				
AG	−0.17	0.04	0.31	0.04	0.43	0.09	1.00			
TwB	−0.16	0.17	−0.26	0.17	0.10	0.11	0.15	1.00		
RGDP	−0.34	−0.05	0.40	−0.05	−0.07	−0.05	−0.10	−0.25	1.00	
INF	−0.22	0.05	0.30	0.05	−0.07	0.12	−0.01	−0.07	0.79	1.00

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