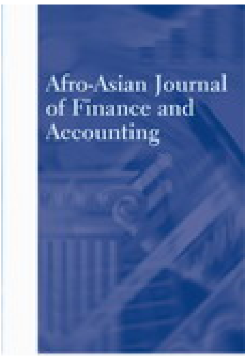

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Default prediction for audited and unaudited private firms under economic and financial stress: evidence from Zimbabwe

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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.

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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, abundant literature has focused on default prediction models for listed corporates in developed economies for which reliable default data and information is widely available (see 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 of it is dedicated to advanced economies. Much less attention has been devoted to the predictor variables of default probability for private firms in developing economies (see for instance, Charalambakis and Garrett, 2019; Takahashi et al., 2018). Restricted research on the determinants of default probability for private corporations is due to the fact that default data and information for such 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 (see Ashraf et al., 2019; Kliestik et al., 2018; Rylov et al., 2016) since the economic structures of these economies are considerably dissimilar (Rylov et al., 2016; Fedorova et al., 2013).

Examining the drivers of default probability for private corporations in undeveloped markets is vital due to some reasons. Private firms are the dominant corporate legal form in developing countries (Charalambakis and Garrett, 2019; Slefendorfas, 2016), possibly due to undeveloped local equity markets in these countries. It has emerged that private firms promote financial and technological innovations, reduce unemployment and promote economic growth and development (Charalambakis and Garrett, 2019; Hyder and Lussier, 2016; Organisation for Economic Co-operation and Development, 2015; Charalambakis, 2014; Halabi and Lussier, 2014; Wymenga et al., 2012). Existent literature reveals that private firms are dissimilar to public firms. Compared to public firms, private firms are smaller in size, use more leverage, depend more on trade credit and bank loans, invest more and are characterised by higher borrowing costs (see for example, Gao et al., 2012; Michaely and Roberts, 2012). Falkenstein et al. (2000) the credit risk for the US privately-owned companies and discovered that the association between default risk and financial variables differs significantly across publicly-traded and privately-owned corporates.

Charalambakis and Garrett (2019) proposed 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 company borrowers accessed from banks are the primary sources of default data and information for private firms. The performance of private firm default prediction models provides more insights into the ability of financial ratios to forecast firm default. In several jurisdictions, there are no legal requests for private firms to divulge their financial results and produce audited financial statements even though some do (Minnis and Shroff, 2017). Financial ratios that are used in private firm default prediction are extracted from audited and unaudited financial statements. Of late, financial institutions, especially commercial banks, have been demanding private firms to submit their audited financial statements before granting any loans and facilities to them. 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. It has emerged that corporations with audited financial statements pose a lower default risk to creditors than their unaudited counterparts (Cenciarelli et al., 2018; Gul et al., 2013).

The corporate default probability is influenced by the general economic conditions that are reflected by macroeconomic variables. Basel II/III advanced ratings-based approach and new accounting standards such as International Financial Reporting Standard 9: Financial Instruments 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. However, the predicament is that there is a lack of industry consensus on which macroeconomic factors have the most substantial impact on corporate default risk under downturn conditions, resulting in the creation of diverse default probability forecasting models.

Against this backdrop, this paper develops stepwise logistic regression models based on different amalgamations of firm and loan characteristics, financial ratios and macroeconomic variables to separately examine drivers of default probability for Zimbabwean audited and unaudited non-financial privately-owned firms under distressed economic and financial conditions twelve months in advance. Hayden (2011) and Basel Committee on Banking Supervision (1999) propounded that a twelve-month period permits financial institutions to take corrective actions to avoid forecasted defaults and ensures that timely data is incorporated into the rating techniques. This research paper's primary focus is on the identification and economic interpretation of the estimated coefficients for the predictor variables incorporated into the designed models. For pertinence and effectiveness reasons, the study applies two unique real-world datasets of defaulted and non-defaulted loan accounts for 308 audited and 301 unaudited non-financial private firms gathered from a major anonymous Zimbabwean commercial bank over the observation period from 2010 to 2018. Geographically, the sample datasets are an accurate depiction of the Zimbabwean market.

Zimbabwe provides an interesting and challenging case in examining default risk for private firms in developing economies. It is a developing economy where private firms dominate and has been undergoing rare, severe and extended distressed economic and financial conditions over the past two decades. 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 firms with an asset value of USD 500,000.00 or more to cede at least 51% of their shares to indigenous Zimbabweans. Therefore, the majority of Zimbabwean private firms are owned by indigenous people. 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 high borrowing costs (due to their low creditworthiness). To fix the economy, the government adopted a bucket of currencies, which included euro, South African rand, British pound, Botswana pula and US dollar and phased out the Zimbabwean Dollar in 2009. However, the US dollar emerged as a major currency and has been used as the functional and presentation currency for companies. Masiyandima et al. (2018) posited that the emergence of the US dollar as the main currency resulted in negative and low inflation rates, impacting the country's growth negatively. During the sample period, World Bank Group (2020) indicated that real GDP growth rate fell from more than 10% per annum in the period 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. Distressed The distressed economic and financial conditions that have been observed in Zimbabwe are seldom found in developed and undeveloped economies.

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 have been operating in Zimbabwe. Commercial banks have been dominating the Zimbabwean banking sector with special reference to total deposits, total assets and total loans and advances. 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 has been spread amongst the 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 to align themselves with global regulatory standards. The RBZ is leading the Basel II implementation process. Nevertheless, some 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 ratio best explain the default probability for Zimbabwean audited and unaudited private firms. These models are associated with 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 Zimbabwean audited private firms. 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 Zimbabwean unaudited private firms.

This paper's results provide compelling evidence showing that accounting information is useful in separating defaulted private firms from non-defaulted ones in the context of distressed financial and economic conditions. The nominated input financial ratios are imperative because they denote some of the most imperative credit risk drivers, i.e., profitability, leverage, growth, and liquidity. This study also indicates that the inclusion of macroeconomic variables improves model fit and the in-sample prediction performance of default models. This implies that firm-and-loan-characteristics, accounting-data and macroeconomic-information based models best explain default probability for Zimbabwean audited and unaudited non-financial private firms. Furthermore, the study reveals that the drivers of default risk for audited and unaudited Zimbabwean non-financial private firms are not the same.

The rest of the study is designed as follows. Section 2 outlines the literature review and Section 3 presents a brief overview of the methodology. In Section 4, data and variables are described and Section 5 is allocated to experimental results. Section 6 presents the discussion of results and Section 7 outlines robustness checks for the designed models. Section 8 concludes the analysis, provides the implications of the study and presents potential directions for future research.

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 (Guotai et al., 2017), genetic algorithms (Zelenkov et al., 2017), recursive partitioning (Frydman et al., 1985), hazard models (Gupta, 2017) and machine learning methods (Barboza et al., 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 (see for instance, Bauer and Agarwal, 2014; Tinoco and Wilson, 2013; Agarwal and Taffler, 2008; Shumway, 2001). Corporate default forecasting literature for developing economies (see for example, Kwak et al., 2012) and for privately-owned companies (see for instance, Charalambakis and Garrett, 2019) is generally restricted. Limited evidence on private firm default prediction is substantially dedicated to advanced markets (see Diekes et al., 2013; Cangemi et al., 2003; Falkenstein et al., 2000). Applying models constructed for developed countries in emerging markets does not always produce plausible results due to many reasons which include the following (see Ashraf et al., 2019). The economic structures of developed and undeveloped economies are significantly different (Liang et al., 2015; Fedorova et al., 2013). Waqas and Md-Rus (2018) articulated that it is imperative to recognise that developed economies are associated with clearer bankruptcy laws and procedures than undeveloped economies. In the same vein, Altman (2018), Takahashi et al. (2018) and Slefendorfas (2016) pronounced that each economy has its unique features, and thus, models developed specifically for individual countries outperform universal 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 default event will remain the same in the time to come. However, this supposition would not remain unchanged over long periods given a wide range of possible events that can take place in financial markets, e.g., changes in accounting policies of companies, financial and economic crises, the introduction of regulatory documents, etc. (see Takahashi et al., 2018; Singh and Mishra, 2016; Smaranda, 2014; Hayden, 2011). Owing to changes in periods, financial situations and economic conditions, the applicability and predictive performance of the existing bankruptcy detection techniques under new settings is a practical inquiry that needs to be addressed in modern finance (see Altman, 2018; Timmermans, 2004). Takahashi et al. (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. In 2016, Singh 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.

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

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 et al., 2018). Huq et al. (2018), Cassar (2011) and Minnis (2011) posited that firms that present audited financial statements to creditors are characterised by lower cost of debt than corporates that do not. The cost of debt indicates the probability of default associated with the borrower. Generally, the higher the cost of debt, the bigger the default risk and the converse is true. Thus, corporates with audited financial statements pose lower default risk to creditors than their unaudited counterparts (Cenciarelli et al., 2018; Gul et al., 2013). Auditing firms can avert corporate bankruptcies (Cenciarelli e al., 2018). Among other things, they can address the issues related to accounting frameworks inadequacy and financial regulations mediocrity which are some of the drivers of corporate failure. Inadequate accounting frameworks, mediocre financial regulations and suboptimal productivity are some of the major causes of corporate failure (Jahur and Quadir, 2012). Cenciarelli et al. (2018) and references therein posited that big auditing firms have the prowess and skills 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, Hamzani and Achmad's (2018) finding suggestively support the supposition that audited firms are associated with low rates of default.

Economic downturns are associated with high default frequencies (Mihalovic, 2016; Canals-Cerda and Kerr, 2015; Leow and Crook, 2014). Basel II/III advanced ratings-based approach and new accounting standards such as International Financial Reporting Standard 9: Financial Instruments have provided 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). Using Cox models, Jensen et al. (2017) posited that macroeconomic factors and accounting ratios are crucial in default forecasting for Danish privately-owned firms. The authors proposed that the firm-specific factors' effects remain robust to the addition of the macroeconomic variables. Jensen et al. (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. It is widely documented that the inclusion of macroeconomic factors improves the model fit and the forecasting ability of default models (Charalambakis and Garrett, 2019; Crook and Bellotii, 2013; Bellotii and Crook, 2009).

3 Methodology

Corporate default is a dichotomous variable. Thus, a binary stepwise logistic regression model is applied to forecast the probability of default. Probability of default, $P_i(z)$, is given by

$$P_i(z) = \exp(z_i) / (1 + \exp(z_i)),$$

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

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

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.

The study adopts a logit model because it provides several benefits. Logistic regression has been extensively applied in corporate default prediction mainly due to its ease-to-use nature, reliability and high predictive performance (see for instance, Kovacova and Kliestikova, 2017). Kliestik et al. (2015) and references therein also indicated that logistic regression is flexible when using real-world data since it does not assume a normal distribution, linearity and independence among independent covariates. Logistic regression has less restrictive statistical requirements than other statistical models such as multiple discriminant and probit models (Obradovic et al., 2018; Kliestik et al., 2015).

4 Data and variables

Two unique real-world datasets of defaulted and non-defaulted loan accounts for audited and unaudited non-financial 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 when an obligor is not likely to settle up 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). Dataset I consists of defaulted and non-defaulted loan accounts for audited private firms while dataset II contains defaulted and non-defaulted loan accounts for unaudited private firms. Initially, dataset I comprises of 315 audited private firm loan accounts and dataset II encompasses 309 unaudited private firm loan accounts. The datasets 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. Conceptually, 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.

The study guarantees that the

1 financial statement data of sample corporates is valid, and henceforth, default analysis is objective

2 sample data is free from general errors

3 datasets are made up of only homogeneous observations, and as a result, the association between the covariates and the default event is comparable

4 default event adopted in developing the logit models is similar to the default event the designed models can forecast

5 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 datasets adopted in this analysis is in line with that in the existent research literature (see Sabela et al., 2018 and references therein). 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 research paper 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 1), six firm and loan characteristics (Table 2) and six macroeconomic factors (Table 3).

Table 1 Financial ratios

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

Notes: Several ratios (such as the current liabilities/total assets and current assets/total assets ratios) show varied financial characteristics of borrowers. The analysis also includes dynamic ratios that relate current to past levels of specific balance sheet entries, e.g., the ratio of total liabilities/total liabilities last year, etc. Hayden (2011) articulated that dynamic ratios are critical in detecting default probability. Financial ratios adopted in this paper denote significant drivers of default risk, i.e., leverage growth, leverage, profitability, liquidity, productivity, turnover, growth, activity and firm size.

Source: Authors' compilation (2020)

The last set of financial statements filed a year before default by defaulted firms is examined in computing their respective financial ratios. In calculating financial ratios for non-defaulted firms, their latest financial statements filed are analysed. Firm and loan characteristics are collected at the time of loan application and macroeconomic variables are obtained from the World Bank Group. Tables 1 to 3 also show the anticipated associations involving default probability and the predictor variables. A positive sign (+) shows that if the value of the predictor variable rises, the default probability increases. Contrariwise, a negative sign (–) displays that if the value of the driver increases, the default probability decreases.

Table 2 Firm and loan characteristics

Abbreviation	*Variable*	*Expected effect*
LN	Loan amount	+
INT	Interest rate	+
AG	Age of the firm	–
CTV	Collateral value	–
TwB	Time with the bank	–
LMP	Loan maturity period	+

Notes: Private firm loans mentioned here are commercial loans which omit 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 firm's age (in years) since the time of its incorporation to the time of loan application. The collateral value represents the value of collateral lodged by the firm client. Collateral types 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.

Source: Authors' compilation (2020)

Table 3 Macroeconomic factors

Abbreviation	*Macroeconomic factor*	*Expected effect*
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	+

Notes: Table 3 reports macroeconomic variables and their expected effect on private firm default probability incorporated into the research work.

Source: Authors' compilation (2020)

Missing data may compromise inferences. Thus, missing data need to be appropriately handled. 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 sample size and is easy to understand and apply. Under this approach, the average of the non-missing values for each driver of default probability with missing value/s is calculated. Each missing value is then substituted with the computed average. In the dataset 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% firms 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 dataset II, the ratio of short-term debt/total assets, the ordinary business income/total assets ratio, the ratio of accounts payable/net sales the interest rate are each missing 0.33% of their values, transforming into 0.66% firms with missing values. It is detected 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 private firm datasets. Outliers can considerably bias the estimated model parameters and result in inappropriate inferences. The study winsorize extreme values at the distribution's 1st and 99th percentiles to avoid removing the outliers from the samples.

Table 4 Financial ratios for audited firms with descriptive statistics

Variable	*Min*	*Max*	*Mean*	*Std. dev.*
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

Notes: * represents figures in millions US dollars.
Table 4 presents the minimum, maximum, mean and standard deviation values for the financial ratios based on the whole sample of audited privately-owned firms.

Source: Authors' computation (2020)

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

Variable	*Min*	*Max*	*Mean*	*Std. dev.*
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

Notes: * represents figures in millions US dollars.
Table 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 firms.

Source: Authors' computation (2020)

Table 6 Macroeconomic factors for audited firms with descriptive statistics

Variable	*Min*	*Max*	*Mean*	*Std. dev.*
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

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

Source: Authors' computation (2020)

Tables 4, 5 and 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 7 Financial ratios for unaudited private firms with descriptive statistics

Variable	*Min*	*Max*	*Mean*	*Std. dev.*
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

Notes: * represents figures in millions US dollars.
Table 7 presents the minimum, maximum, mean and standard deviation values for the financial ratios based on the sample of unaudited privately-owned firms.

Source: Authors' computation (2020)

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

Variable	*Min*	*Max*	*Mean*	*Std. dev.*
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

Notes: * represents figures in millions US dollars.
Table 8 outlines the minimum, maximum, mean and standard deviation values for the firm and loan characteristics based on the entire sample of unaudited private firms.

Source: Authors' computation (2020)

Table 9 Macroeconomic factors for unaudited firms with descriptive statistics

Variable	*Min*	*Max*	*Mean*	*Std. dev.*
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	–11.20	–1.10	–2.65	2.79
PDE	37.10	54.20	44.03	6.55
UR	4.90	5.60	5.35	0.22

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

Source: Authors' computation (2020)

Tables 7, 8 and 9 outline the descriptive statistics for financial ratios, firm and loan characteristics and macroeconomic variables, respectively, for the entire sample of unaudited private firms.

5 Experimental results

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 whereas the probability needed for a risk factor to be excluded from the equation is gazetted at 0.20. This stepwise threshold incorporates all statistically significant covariates related to the response variable (Hosmer and Lemeshow, 2000). To resolve the multicollinearity challenge, 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:

Model I Model I is designed using financial ratios and firm and loan characteristics to analyse default risk for audited private firms.

Model II Model II is developed based on financial ratios, firm and loan characteristics and macroeconomic factors in order to examine default probability for audited private corporates.

Model III Model III is created using financial ratios and firm and loan characteristics to predict default probability for unaudited private companies.

Model IV Model IV is built based on financial ratios, macroeconomic variables and firm and loan characteristics in order to forecast default probability for unaudited private firms.

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 × 2 classification matrix (see Table 10) with that reveals the following four outcomes is employed to describe the performance of the models: true positive (TP): class of a defaulted firm correctly selected as a defaulted firm; false positive (FP): category of a non-defaulted firm wrongly chosen as a defaulted firm; false negative (FN): class of a defaulted firm wrongly pinpointed as a non-defaulted firm; and true negative (TN): category of a non-defaulted firm rightly identified as a non-defaulted firm.

Table 10 The 2 × 2 classification matrix for a classification problem

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

Notes: Where ON = observed negative = FP + TN, OP = observed positive = TP + FN, PN = predicted negative = FN + TN, PP = predicted positive = TP + FP and TOTAL = TP + FP + FN + TN.

The employs the in-sample classification rates and Type I and Type II error rates to assess the generated models' performance. Basically, the classification rate shows the proportion of firms 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-defaultedThe in-sample classification rates and Type I and Type II error rates for the designed stepwise logit models are determined determined for cut-off points cut-off points from 0.1 to 0.9 at the 10% significance level. Explicitly, the classification rates and Type I and Type II error rates are determined as follows:

$$\text{Classification rate} = (\text{TP} + \text{TN})/\text{TOTAL}$$

$$\text{Type I error rate} = \text{FP}/(\text{FP} + \text{TN}),$$

$$\text{Type II error rate} = \text{FN}/(\text{FN} + \text{TP}).$$

5.2.1 Model I

Table 11 outlines the in-sample classification rates, Type I error rates and Type II error rates for Model I.

Table 11 Cut-off points, classification rates, Type I error rates 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

Source: Authors' computation (2020)

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% and Type II error rates run from 0% to 100%. Existent literature has proposed several ways of selecting optimal cut-off points (see for instance, Sabela et al., 2018 and references therein). This research article chooses cut-off points at which the sum of the Type 1 error rate and Type II error rate is minimal and the overall model performance is high as the optimal cut-off points. In this case, cut-off points 0.3 and 0.4 are associated with the minimal sum of the two errors, 8.33% + 0% (8.33%), and a high model 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.

5.2.2 Model II

Table 12 indicates 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%. Cut-off point 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 classification rate of 96.40%. Interestingly, Model I has a classification rate of 92.90% while Model II has a classification rate of 96.40%, indicating that the inclusion of macroeconomic variables improves the predictive capacity of the default models for Zimbabwean audited private firms.

Table 12 Cut-off points, classification rates, Type I error rates 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

Source: Authors' computation (2020)

5.2.3 Model III

Table 13 indicates the in-sample classification rates, Type I error rates and Type II error rates for Model III. It reveals that the 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%. Cut-off point 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 classification rate of 86.00%.

Table 13 Cut-off points, classification rates, Type I error rates 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

Source: Authors' computation (2020)

5.2.4 Model IV

Table 14 indicates the in-sample classification rates, Type I error rates and Type II error rates for Model IV.

Table 14 Cut-off points, classification rates, Type I error rates 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

Source: Authors' computation (2020)

Table 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% whereas Type II error rates range from 0% to 57.14%. Cut-off point 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 classification rate of 93.00%. Fascinatingly, Model III has a classification rate of 86.00% while Model IV has a classification rate of 93.00%, signifying that the incorporation of macroeconomic factors enhances the forecasting ability of the default prediction models for Zimbabwean unaudited privately-owned firms.

6 Discussion

This section discusses the results of each developed model. To evaluate the significance of the determinants of the default probability for Zimbabwean audited and unaudited private firms 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 variable is below the 5% confidence level (typically $p \leq 0.05$), it indicates that the variable notably contributes to the forecasting capacity 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 shows 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.

6.1 Model I

Table 15 presents variables, with their corresponding p-values based on the Wald test, incorporated into Model I.

Table 15 Model I results reflecting coefficient estimates

Variable	*Coefficient*	*Wald*	*Sig.*
(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

Source: Authors' computation (2020)

It has emerged that there are no substantial correlations between the predictors included in Model I as indicated in Table 16. Hence, Model I is not influenced by multicollinearity.

The empirical results indicate that all drivers included in Model I are greatly linked to the default probability for Zimbabwean audited private firms 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 negative signs while 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 have positive signs.

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, see for example, Bauer and Edresz (2016), Charalambakis and Garrett (2016), Charalambakis (2015), Charalambakis (2014), Hayden (2011), Ohlson (1980) and Shumway (2001), etc. Charalambakis and Garrett (2019) found a negative correlation between financial distress probability and profitability for Greek private firms. Using a massive sample of bank loans to private Danish firms, Jensen et al. (2017) confirmed that profitability is negatively associated with the probability of default. Likewise, Durica et al. (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. Furthermore, Altman et al. (2010) found a negative relationship between the financial distress probability and profitability for United Kingdom (UK) SMEs while Altman and Sabato (2007) revealed a negative correlation between the probability of financial distress and profitability for US SMEs.

Table 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

Source: Authors' computation (2020)

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 falls. As a liquidity ratio, the (current assets-current liabilities)/total assets 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 et al. (2010) and Altman and Sabato (2007) for UK and US SMEs, respectively. In the study by Jensen et al. (2017), the quick ratio, which is a measure of liquidity, has 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 et al. (2019) discovered a negative association between the (current assets-current liabilities)/total assets ratio and the business 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. 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 et al. (2016), Succurro and Mannarino (2013) and Chava and Jarrow (2004), it has emerged that the age of the firm enters Model I with a negative sign, indicating that young and adolescent firms are characterised by higher default risk than mature and established corporates. Mature and established Zimbabwean non-financial 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. Young and adolescent Zimbabwean 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, incapability to adjust to environmental wishes and poor managerial skills. Moreover, youthful Zimbabwean private firms 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. 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. On the other hand, Switzer et al. (2018) proffered that firm age and default risk are positively associated. Moreover, some studies have found no projecting power for the age of the company in bankruptcy prediction (see Situm, 2014; 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, the default probability rises. Jensen et al. (2017) confirmed that the leverage for Danish private firms and default probability are positively related. Altman et al. (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 harder throughout a financial and economic crisis in which capital restraints are indispensable. The adoption of high leverage also reduces private firms' cover against adverse shocks. In support of this, Falkenstein et al. (2000) posited that the greater the leverage used by firms, the lower the cushion against antagonistic shocks. The adoption of more debt by Zimbabwean private firms 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. Furthermore, credit comes at a cost which negatively affects customers' ability to repay debts (see for instance, Aleksanyan and Huiban 2016). Given that several Zimbabwean private firms 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. That is to say, 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 private firms with long-term lending associations with their banks before loan acquisition are linked with a low probability of default. Zimbabwean private corporates with long-term associations with their banks are better able to survive downturn conditions than corporates with short-term associations with their banks. Long-lasting credit relationships offer stability to obligors in the context of distressed economic and financial conditions because they get assurance to get credit from banks under such circumstances and profit from low prices for services provided by the banks and reduced loan interest rates. A guarantee from a bank to access credit increases the availability of financial resources when firms witness temporary shortfalls in revenue under illiquid conditions. Zimbabwean private firms with long-term associations with banks can renegotiate their credit conditions as well. Moreover, durable firm-bank credit relationships alleviate enticements, on the part of the obligors, to dissuade funds to non-core business activities, thereby reducing the default probability. Using a large sample of bank loans to private Danish companies, Jensen et al. (2017) found a negative correlation between the age of the banking relationship and 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 borrower and bank generates value to the borrowing firm in the form of, among other benefits, guarantee to get credit and low interest rates. Bodenhorn (2003) proffered that firms with long-term firm-bank associations profit from less personal guarantees required when borrowing, lower costs of credit and renegotiable loan terms during a credit crunch. Suggestively, Bodenhorn (2003), Peltoniemi (2007) and Petersen (1999) showed that corporates with long-term firm-bank associations are linked with a low probability of default.

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. This ratio measures the stability of a corporate's performance. 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 desirable, in practice, for a corporate to grow up instead of scaling down. 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 net sales/net sales last year. Bauer and Edresz (2016) further promulgated 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 enters Model I with a negative sign, the study reveals that this ratio is linked with a positive regression coefficient. That is to say, the probability of default increases as the ratio rises. This finding is against intuition. However, this outcome is motivated by the denominator 'total liabilities' rather than the numerator 'earnings before interest and tax'. The high levels of the ratio of earnings before interest and tax/total liabilities are a product of low levels of total liabilities as a result of low levels of trade credit. Several Zimbabwean private firms are of low creditworthiness and are embroiled in debt. Thus, they cannot merely acquire formal credit from financial institutions, especially banks. As a substitute for formal credit from financial institutions, they depend more on suppliers' trade-credit. Nevertheless, financially distressed corporates find it challenging to get suppliers' trade-credit to maintain 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 promulgated that suppliers offset credit reduction from financial institutions when granting trade-credit to low creditworthy corporates. Bastos and Pindado (2013) also proposed that suppliers provide trade credit for a short time before they become credit restricted and reduce the level of trade credit during financial crises. Generally, in Zimbabwe, supplier firms have restricted access to formal credit from financial institutions due to the prevailing liquidity crisis. This results in them having lower cash holdings, which translates into condensed trade-credit levels to client firms. Under the same line of reasoning, Shenoy and Williams (2017) posited that supplier firms with more access to bank liquidity offer more trade-credit to their clients and the opposite is true. Given that no other credit source is accessible 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, the research work discovers 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 is against intuition. Nonetheless, this outcome is more motivated by the numerator 'current assets' than the denominator 'total assets'. Most Zimbabwean private firms use suppliers' trade-credit as they cannot purchase goods and services on restricted terms such as cash on delivery (COD) and and cannot easily access bank credit due to the extended liquidity squeeze in the economy. This has a grave influence on the firms' ability to operate. Consequently, a myriad of private firms is associated with high levels of accounts receivable, which they cannot gather timeously. If a trade debtor falls into default, losses witnessed by the trade creditor leads it into default. Private corporates with high accounts receivable end up postponing or failing to meet their credit obligations, resulting in a credit contagion cascading effect. Jacobson and Schedvin (2015) indicated that trade creditors witness substantial trade credit losses owing to trade debtor failures and bankruptcy risks for creditors rise in the magnitude of assumed losses. In the same vein, Bastos and Pindado (2013) suggested that a trade-credit contagion frequently happens in the supply chain during a financial crisis. Jorian and Zhang (2009) established that trade credit interfaces could transfer credit contagion in industrial firms.

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, the 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 as a result of customers' inability to buy goods on restricted terms such as COD due to the liquidity calamity in the economy. Credit restraints in the country cause private firms holding high-levels of accounts receivable to delay payments to their creditors, thereby creating default risk for private firms. High levels of accounts receivable adversely affect the profitability, liquidity and cash flow positions of firms since they cannot be collected in time. Furthermore, 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. Monteiro (2014) articulated that credit restrictions during a financial crisis cause companies holding high-levels of accounts receivable to defer payments to suppliers. Under 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) propagated that trade credit relations can send credit contagion across industrial firms.

6.2 Model II

Table 17 outlines variables, including their p-values based on the Wald test, included in Model II.

Table 17 Model II results reflecting coefficient estimates

Variable	*Coefficient*	*Wald*	*Sig.*
(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

Source: Authors' computation (2020)

There are no considerable correlations between the predictors incorporated into Model II as indicated in Table 18. Consequently, Model II is not affected by multicollinearity.

Table 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

Source: Authors' computation (2020)

The experimental results show that all variables included in Model II are substantially linked with the default probability for Zimbabwean audited private 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 negative signs while the ratios of earnings before interest and tax/total liabilities, short-term debt/total assets, current assets/total assets and bank debt/total assets have positive signs. 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 Zimbabwean audited private firms.

Empirical findings reveal 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 firms are negatively correlated. On the other hand, Jensen et al. (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 is against intuition, indicating that as the inflation rate rises, the probability of default falls. However, this result can be explained. The sample period under contemplation is associated with a deflation. In Zimbabwe, a deflation resulted in reduced overall economic activity, a decrease in investment, an increase in debt's real value and a surge in unemployment rates (see for example, Mahonde, 2016). Masiyandima et al. (2018) propounded that the advent of the US dollar as the main currency in Zimbabwe resulted in negative and low rates of inflation, which adversely affected the country's growth. A deflation has heightened the recession in Zimbabwe and led to a deflationary spiral. The rise in the real value of debts due to a deflation made it difficult for Zimbabwean private firms to repay outstanding loans, leading to high default rates. Conversely, Jensen et al. (2017) posited that inflation does not influence the Danish private firms' default probability.

6.3 Model III

Table 19 outlines variables, including their p-values based on the Wald test, incorporated into Model III.

It is noticed that there are no considerable correlations between the predictors incorporated into Model III, as shown in Table 20. Hence, Model III is not affected by multicollinearity.

The empirical results show that all variables included in Model III are substantially related with the probability of default for Zimbabwean unaudited private 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 and the (net sales-material costs)/personnel costs ratio having the negative effect while 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 have positive signs. 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.

Table 19 Model III results reflecting coefficient estimates

Variable	*Coefficient*	*Wald*	*Sig.*
(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

Source: Authors' computation (2020)

It has emerged that a measure of productivity, i.e., the ratio of (net sales-material costs)/personnel costs is associated with a negative coefficient, indicating that as the ratio increases, the 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 converse is correct. Aleksanyan and Huiban (2016) articulated that company productivity is a crucial determinant of bankruptcy and revealed that productivity positively influences corporate default probability. Furthermore, Jahur and Quadir (2012) propounded 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 also increases. In Zimbabwe, older and mature unaudited private firms mainly fail due to lack of strategic foresight, increased competition, innovativeness inflexibility, economic slowdowns, costly organisational frameworks, high-cost pressures and a lack of adaptability. This result is in agreement with the findings of Switzer et al. (2018), Kucher et al. (2018) and Aleksanyan and Huiban (2016). Kucher et al. (2018) propounded that mature SMEs fight more with amplified competition and economic downturns. Furthermore, Succurro and Mannarino (2013) postulated that empirical studies in advanced countries found a negative correlation between bankruptcy and age while research in developing countries indicated contradictory results.

Table 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*	*AG*	*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		
AG	–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

Source: Authors' computation (2020)

The study finds compelling evidence indicating that the interest rate has a significant impact on the default probability for unaudited 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 private firms. 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) articulated that due to high interest rates, several firms can fail to repay their loans to the banks. Moreover, Gonzalez-Aguado and Suarez (2011) propounded that, in the short-run, increases and decreases in interest rates escalate the firm default rate. The authors further posited that, in the long run, high interest rates lead to low firm default rates because high interest rates encourage low 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. The authors do 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 Zimbabwean unaudited non-financial private corporations and the ratio of net sales/net sales last year is positive, indicating that as the ratio increases, default probability rises. It is desirable, in reality, for a corporate to grow up instead of scaling down. However, the high growth of sales is a significant source of high default risk, as indicated here. Private firms in Zimbabwe 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 massive closures of local corporations due to perennial viability problems. Given that the majority of the Zimbabwean private firms are owned by the indigenous people with limited management abilities, the owners find it challenging to cope with the management challenges that come into existence as a result of the rapid growth, resulting in high default frequencies. Moreover, the rapid growth of sales has been financed through debt, which is challenging to service for several private firms due to their continuous viability problems and vulnerability to idiosyncratic shocks. Under 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 grow up very rapidly might fail to solve the management difficulties that come into existence as a result of swift growth. Falkenstein et al. (2000) also propounded that high growth of sales implies that a corporate is rapidly growing and that rapid growth is unlikely to be financed by generated profits, increasing debt and other associated risks such as bankruptcy.

6.4 Model IV

Variables incorporated into Model IV are presented in Table 21.

Table 21 Model IV results reflecting coefficient estimates

Variable	*Coefficient*	*Wald*	*Sig.*
(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

Source: Authors' computation (2020)

This study reveals that there are no significant correlations between the predictors included in Model IV, as indicated in Table 22. Thus, Model IV is not influenced by multicollinearity.

The empirical results show that all drivers of default probability incorporated into Model IV are significantly related with the probability of default for Zimbabwean unaudited private 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 the negative effect while 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 have positive signs. 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, II and III. The inflation rate and real GDP growth rate behave as in Model II while the interest rate and net sales/net sales last year ratio act as in Model III.

Table 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

Source: Authors' computation (2020)

7 Robustness checks

Omnibus tests, pseudo R^2 measures (i.e., Cox and Snell R^2 and Nagelkerke R^2) and Hosmer and Lemeshow tests are implemented to examine the robustness of the developed models.

7.1 Omnibus tests of model coefficients

Omnibus tests results are summarised in Table 23.

Table 23 Omnibus tests of model coefficients

		Chi-square	*df*	*Sig.*
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

Source: Authors' computation (2020)

The omnibus test reveals how well the created logit models perform. If the model's omnibus test p-value is less than the 5% level of significance, the model is statistically significant. It is observed that the omnibus test p-values for all the designed models are below the 5% level of significance, indicating that the models are well fitted to the data and the included variables are statistically significant.

7.2 Pseudo R^2 measures

Table 24 outlines the values of the pseudo R^2 measures (i.e., Cox and Snell R^2 and Nagelkerke R^2) for the models.

Table 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

Source: Authors' computation (2020)

The Cox and Snell R^2 and Nagelkerke R^2 values indicate how much of the variance in the response variable is explained by the created model. Explicitly, the Nagelkerke R^2 measure indicates that Model I explains 65.90% of the variance of the response variable whereas the Cox and Snell R^2 measure shows that Model I describes 36.90% of the dependent variable variance. Conclusively, the predictors incorporated into Model I explain between 36.90% and 65.90% of the variance of the response variable. Under the same line of thinking, Model II describes between 48.20% and 86.20% of the variance of the dependent variable while Model III explains between 48.00% and 67.00% of the variation of the response variable. Lastly, Model IV describes between 54.60% and 76.20% of the variance of the dependent variable. The Cox and Snell R^2 and Nagelkerke R^2 values show that the designed logistic regression models are regarded as good models.

7.3 Hosmer and Lemeshow test

The Hosmer and Lemeshow test results of the developed models are presented in Table 25.

Table 25 Hosmer and Lemeshow tests for the generated models

	Chi-square	*df*	*Sig.*
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

Source: Authors' computation (2020)

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

8 Conclusions and implications of the study

Corporate default prediction has been attracting a lot of scientific and regulatory attention due to the occurrence of the 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 default, the forecasting of default probability for private firms in developing economies is a vital and understudied zone in credit risk management. Consequently, this research article proposes and analyses four stepwise logistic regression models to separately detect default probability for Zimbabwean audited and unaudited private firms under economic and financial stress twelve months in advance. The study's primary focus is on identifying and interpreting the coefficients of the selected predictor variables.

The research paper offers considerable evidence indicating that models including firm and loan characteristics, macroeconomic factors and accounting information best explain the default probability for Zimbabwean audited and unaudited private firms. These models are characterised by 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 Zimbabwean audited private firms. 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 Zimbabwean unaudited private firms.

This paper'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. This implies that financial statements are imperative in forecasting default probability for audited and unaudited private firms. Moreover, the study indicates that the inclusion of macroeconomic variables improves model fit and the in-sample prediction performance of default models. This implies that firm-and-loan-characteristics, accounting-data and macroeconomic-information based models best explain default probability for audited and unaudited private firms under distressed economic and financial conditions. Therefore, it is recommended that firm and loan features, accounting information and macroeconomic variables must be incorporated when predicting default probability for private firms under downturn conditions. 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 default risk for audited and unaudited private firms separately from a risk management perspective.

Predicting default probability for privately-traded firms is imperative because it helps financial institutions create policies linked to the provision of credit and the cost of credit to private firms. Default risk is crucial in generating the prices and yields of financial assets. Furthermore, the analysis of financial institutions' risk exposure towards private firms is of interest to macroprudential and microprudential supervisors. The results are vital for decision-makers to stimulate macroeconomic growth and development. Given the financial and economic significance of private firms for the Zimbabwean economy, the results of this study also offer a political and economic validation for the separate assessment of default risk for audited and unaudited private firms.

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

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