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Corporate Loan Recovery Rates under Downturn Conditions in a Developing Economy: Evidence from Zimbabwe

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Abstract: In this study, we design stepwise ordinary least squares regression models using various amalgamations of firm features, loan characteristics and macroeconomic variables to forecast workout recovery rates for defaulted bank loans for private non-financial corporates under downturn conditions in Zimbabwe. Our principal aim is to identify and interpret the determinants of recovery rates for private firm defaulted bank loans. For suitability and efficacy purposes, we adopt a unique real-life data set of defaulted bank loans for private non-financial firms pooled from a major anonymous Zimbabwean commercial bank. Our empirical results show that the firm size, the collateral value, the exposure at default, the earnings before interest and tax/total assets ratio, the length of the workout process, the total debt/total assets ratio, the ratio of (current assets–current liabilities)/total assets, the inflation rate, the interest rate and the real gross domestic product growth rate are the significant determinants of RRs for Zimbabwean private non-financial firm bank loans. We reveal that accounting information is useful in examining recovery rates for defaulted bank loans for private corporations under distressed financial and economic conditions. Moreover, we discover that the prediction results of recovery rate models are augmented by fusing firm features and loan characteristics with macroeconomic factors.

Keywords: recovery rates; private non-financial firms; developing economy; determinants; downturn conditions; stepwise ordinary least squares regression model

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1. Introduction

The most crucial credit risk components comprise the probability of default (PD), exposure at default (EAD) and recovery rate (RR) or, equivalently, loss-given default (LGD), i.e., 1-RR. There are several reasons why these components should be examined. They are used in the designing of collection policies to be implemented for defaulted firms, development of risk policies, formulation of credit terms, determination of credit portfolio expected and unexpected losses and computation of capital levels (Hocht et al. 2022; Matenda et al. 2021b; Starosta 2021; Min et al. 2020; Ingermann et al. 2016). In addition, regulators need financial institutions to display evidence of credit risk modelling to warrant that regulatory capital requirements are upheld.

Although substantial research has been directed towards PD estimation, limited research attention has been dedicated to RR modelling (Siarka 2021; Calabrese 2014a; Jankowitsch et al. 2014; Yao et al. 2015; Zhang and Thomas 2012). However, against a backdrop of declining recovery values, lack of quality data on recoveries and defaults, limited relevant predictor variables, emergence of Basel II/III principles, rising numbers of defaulting borrowers due to the recent 2007–2009 global recession, and variations in recovery methodologies adopted by financial institutions, swelling research effort has been directed towards RR computation of late (Hocht et al. 2022; Sopitpongstorn et al.

2017; Yao et al. 2017; Jankowitsch et al. 2014). Accurate estimation of RRs leads to more efficient use of capital and failure to precisely predict RRs in the credit risk process could result in under- or over-provisioning for the forthcoming loan losses (Wang et al. 2020). Ingermann et al. (2016) and Gurtler and Hibbeln (2013) also indicated that appropriate RR models lead to reduced capital requirements, and precise prediction of RRs can produce a competitive advantage to the financial institution and reduces challenges emanating from unfavourable picking owing to minor variances in loan spreads.

This study contributes to the extant literature by examining the determinants of RRs for private non-financial firm defaulted bank loans under economic and financial stress in a developing economy (Zimbabwe). There are a number of reasons why assessing the drivers of RRs for private firm defaulted bank loans under economic and financial stress in a developing country is essential.

First, private corporations are dominant firms in undeveloped markets (Charalambakis and Garrett 2019; Slefendorfas 2016). Hence, bank loans granted to private non-financial firms contribute significantly to the total bank loans. Second, economies are not the same; they differ from each other. Diverse economies are characterised by distinctive characteristics such as rules (e.g., workout process regulatory structures), creditors' rights, regimes of bankruptcy, reorganisation practices and legal systems, which affect recoveries and do not allow the reapplication of RR and LGD models designed in them in different atmospheres (Ingermann et al. 2016; Mora 2015; Shibut and Singer 2015; Peter 2011; Davydenko and Franks 2008; Bris et al. 2006; Querci 2005; Franks et al. 2004). In addition, the economic and regulatory settings of developed and undeveloped markets are not similar. For instance, Waqas and Md-Rus (2018) posited that advanced economies have clearly stated bankruptcy laws and procedures, while undeveloped markets are deficient in such bankruptcy laws and procedures. How emerging and advanced markets allocate recovery risk premiums and the approach in which financial distress is ultimately dealt with generate diverse configurations for RRs across developed and undeveloped economies. The implication is that RRs in developing and developed economies are not influenced by identical variables (see Medhi et al. 2018).

Third, the majority of research papers have proposed RR models for developed economies (Wang et al. 2020; Francois 2019; Ingermann et al. 2016; Khieu et al. 2012), particularly for corporate bonds since data for publicly traded bonds is broadly available (Mora 2015; Jankowitsch et al. 2014; Yao et al. 2015). Nevertheless, literature on bank loan RRs is generally restricted and is even more constrained in undeveloped markets. The main reason is the scarcity of recovery data for bank loans since they are regarded as private debt instruments. Even though literature on bank loan RRs has been increasing of late (Ingermann et al. 2016), the available literature on bank loan RRs is substantially devoted to advanced economies (Ingermann et al. 2016; Khieu et al. 2012). Specifically, literature on private firm RRs is minimal and is significantly focused on developed markets (see Franks et al. 2004). Given that bank loans are significantly different from securities such as bonds and other traded corporate debts (Wang et al. 2020; Acharya et al. 2007; Varma and Cantor 2005; Franks and Torous 1994; Gilson 1990; Gilson et al. 1990), applying RRs models explicitly developed for corporate bonds on corporate bank loans cannot produce dependable results.

Fourth, despite the prevalence of non-performing loans in developing economies, financial institutions in developing countries usually struggle to design RR and LGD models that are extensively implemented in developed countries. Problems include shallow and imperfect financial markets, data inadequacy and insufficient technical capacity.

The recent 2007–2009 global financial and economic crisis has highlighted the multi-faceted and stochastic nature of RRs in the event of default (Jankowitsch et al. 2014). A financial and economic crisis through the resolution time affects the RRs. Therefore, it has been observed that macroeconomic variables, which reflect macroeconomic conditions, should be considered when modelling RRs. Bellotti and Crook (2012) revealed that incorporating macroeconomic factors reduces uncertainty in forecasting RRs since macroeconomic variables capture the effects of distressed economic and financial conditions. Further, although downturn conditions are associated with low RRs, it is not crystal-clear which variables may describe RRs in a better way under these downturn conditions. Betz et al. (2018) declared that the values of LGD are based on RRs generated throughout different economic situations in the resolution process; hence, it is challenging to select relevant macroeconomic factors.

In this study, we suggest stepwise ordinary least squares (OLS) regression models founded on diverse combinations of firm characteristics, loan features and macroeconomic factors to predict workout RRs for defaulted private non-financial firm bank loans under economic and financial stress in Zimbabwe. The study's principal focus is the identification and economic interpretation of the drivers of RRs for private firm defaulted bank loans. Our analysis strives to provide answers to the following research questions:

(i) What are the significant predictor variables of RRs for defaulted private non-financial firm bank loans under downturn conditions in Zimbabwe?
(ii) Does the incorporation of macroeconomic variables result in improved RR models?
(iii) How well do the designed models perform in predicting RRs?

To fit the models, the study adopts a unique real-life cross-sectional data set of defaulted private firm bank loans accessed from a major anonymised Zimbabwean commercial bank from 2010–2018. Geographically, the data set is an accurate picture of the Zimbabwean market. The authors believe that this research article is the first piece of research work to analyse RRs for Zimbabwean privately owned non-financial firm defaulted bank loans.

Zimbabwe provides a challenging and exciting example in examining RRs for defaulted private firm bank loans in developing countries under economic and financial stress. Matenda et al. (2021a, 2021b) promulgated that the country has been experiencing severe and extended downturn conditions over the past two decades, which have promoted deindustrialisation and informalisation of the economy. In 2009, the nation phased out the Zimbabwean dollar and embraced a number of currencies, including the British pound, Botswana pula, euro, South African rand and American dollar, to stabilise the economy (Matenda et al. 2021a, 2021b). Nevertheless, Matenda et al. (2021a, 2021b) propounded that the American dollar materialised as corporations' presentation and functional currency. The advent of the American dollar as the chief currency caused negative and low inflation rates, adversely affecting the nation's growth (Masiyandima et al. 2018). Masiyandima et al. (2018) indicated that the country observed 28 uninterrupted months of negative inflation from October 2014–January 2017. During the period under review, i.e., 2010–2018, the real gross domestic product (GDP) growth rate has fallen from more than 10% per annum in 2010–2012 to an average of 2.5% from 2013–2018 (World Bank Group 2020). Moreover, during the observation period, World Bank Group (2020) indicated that inflation fell from 3% in 2010 to −2.4% in 2015 before rising to 10.6% in 2018, while budget balance and public debt were on average −4.07% of GDP and 43.68% of GDP, respectively. The distressed economic and financial conditions observed in Zimbabwe are hardly experienced in advanced economies or other undeveloped markets. Therefore, the results of this examination can be compared to but must not be expected to be similar to the results of other research efforts in RR modelling.

We discover that there are several important covariates of RRs extracted from firm characteristics, loan features and macroeconomic factors. The experimental results show that the firm size, the earnings before interest and tax/total assets ratio, the EAD, the length of the workout process, the total debt/total assets ratio, the ratio of (current assets − current liabilities)/total assets, the inflation rate, the interest rate, the collateral value, and the real GDP growth rate are all significant determinants of RRs for Zimbabwean private non-financial firm bank loans. Even though it is not trivial to model RRs and model fit is generally poor, we nonetheless discover that models can be designed which generate augmented forecasts of RRs. We observe that accounting information helps examine RRs for defaulted bank loans for private corporations under downturn conditions in a developing economy. The research also reveals that the prediction results of RR models are augmented by including macroeconomic factors, i.e., the inflation rate and the real GDP growth rate. This research result is in line with the discovery of Bellotti and Crook (2012), who posited that RR prediction models' forecasting results are improved by including macroeconomic variables. The inclusion of macroeconomic factors follows the Basel II recommendation to predict the "downturn LGD" because stressed values of macroeconomic factors may be implemented in the models to predict LGD under poor economic circumstances (see Bellotti and Crook 2012).

The prediction of RRs for defaulted bank loans for private firms in a developing economy using macroeconomic variables is a novel area of research. The contributions of this research work are that we (i) predict RRs for private non-financial firm defaulted bank loans under distressed conditions in Zimbabwe, (ii) identify and interpret the determinants of RRs for private non-financial firm defaulted bank loans under downturn conditions in Zimbabwe, (ii) incorporate macroeconomic variables into the designed models and (iii) articulate the outcomes of model assessments. The remainder of the paper is set out below. Section 2 outlines the literature review. The data and methodology are described in Section 3, and Section 4 is devoted to empirical results and analysis. Lastly, Section 5 presents the conclusions of the study.

2. Literature Review

On the one hand, the bulk of extant research work on RRs is significantly devoted to bonds (Mora 2015; Jankowitsch et al. 2014; Yao et al. 2015; Bruche and Gonzalez-Aguado 2010; Schuermann 2004a). On the other hand, the empirical literature concerning the RRs for bank loans is limited owing to the scarcity of data for loan recoveries since loans are regarded as private debt instruments (Calabrese 2014b; Frye 2000). Calabrese and Zenga (2010), Chalupka and Kopecsni (2009), Grunert and Weber (2009) and Dermine and De Carvalho (2006) are some of the authors who consider recovery rate for bank loans.

Mora (2015) stated that RRs diverge significantly across categories of debt instruments. For example, it has emerged that bank loans and bonds are characterised by diverse characteristics that make their respective RRs different. In support of this, several authors (see, for example, Acharya et al. 2007; Schuermann 2004a) observed that bank loans are associated with superior RRs than bonds. Chalupka and Kopecsni (2009) postulated that bank loans are generally at the debt structure summit, entailing higher RRs than bonds. Further, Araten et al. (2004) opined that bank loan LGDs are associated with higher variability levels than bonds' RRs, and Schuermann (2004a) propounded that the opposite is true. Therefore, applying RR models designed for bonds to bank loans may not produce good results.

RRs depend on exogenous variables (macroeconomic factors, e.g., rate of inflation, real GDP growth rate, unemployment rate, etc.), and endogenous variables (firm characteristics, e.g., firm age, number of creditors, total assets, etc., and account features, e.g., age of the account at default, loan amount, collateral value, etc.), (Gambetti et al. 2022; Hocht et al. 2022; Sopitpongstorn et al. 2021; Brumma et al. 2014). Over the years, direct empirical research has been conducted to assess the dynamics and determinants of RRs. Nevertheless, a review of extant literature indicate that it is not trivial to recognise drivers of RRs (Gambetti et al. 2022; Bastos 2010). Gambetti et al. (2022) stated that the operations management problem is to recognise the appropriate forecasting factors and a suitable technique for modelling RRs.

Altman and Kishore (1996) and Asarnow and Edwards (1995) are some of the first authors to incorporate endogenous factors in RR modelling. In their study, Asarnow and Edwards (1995) examined United States (US) structured loans and US commercial and industrial firm loans. They discovered that structured loans are associated with superior RR than commercial and industrial firm loans. Altman and Kishore (1996) assessed the influence of seniority, collateralisation and industry affiliation on individual RRs. In 2021, Amiram and Owens (2021) indicated that accounting metrics obtainable to creditors at the contracting time are revealing as far as future LGD is concerned. Donovan et al. (2015) revealed that lenders of corporates that have more conservative accounting before default are associated with substantially superior RRs. In contradiction to Bastos (2010), Felsovalyi and Hurt (1998) discovered that the RRs for bigger loans are greater.

On yearly RRs, Altman et al. (2001) discovered secondary influences of macroeconomic factors. Hocht et al. (2022) analysed the association between monthly aggregated RRs and diverse exogenous covariates explaining the macroeconomic atmosphere (e.g., unemployment and inflation), stock markets (e.g., SP 500) and interest-rate movements (e.g., Euro Interbank Offered Rates). To do this, Hocht et al. (2022) described the behaviour of monthly aggregated RRs implementing quarterly and monthly macroeconomic factors in a regression framework. The authors (Hocht et al. 2022) discovered that aggregated RR distribution varies between prosperity and crisis periods. Bellotti and Crook (2012) discovered that the unemployment level and bank interest rates substantially impact LGD. Ingermann et al. (2016) opined that inflation and unemployment result in elevated RRs. Covitz and Han (2004) exposed a positive relationship between yearly aggregated RR and GDP and Khieu et al. (2012) revealed a positive relationship between annual GDP growth and RR. Unexpectedly, Felsovalyi and Hurt (1998) postulated that economic variations (indicated by annual GDP growth) and sovereign events do not impact RR. Although numerous studies approved that the economy and RRs are associated, they do not reach an agreement on the fundamental macroeconomic determinants of RRs. Moreover, several authors propounded that during economic downturn situations, RRs are lesser. For instance, Frye (2000) postulated that during crisis periods, RR could drop 20–25% with reference to prosperity periods.

Calabrese (2014a) exposed that macroeconomic factors are pertinent in describing RRs, and they permit the forecasting of RRs under downturn conditions, as Basel II requires. Basel II/III calls for internal forecasts for RRs to incorporate economic downturn conditions where essential to precisely describe credit risk. Nevertheless, in the Basel II/III Advanced Internal Ratings-based (AIRB) approach, there is no methodological precision regarding the models required for estimating RRs. This issue causes variability in the RR models adopted in banks. Under the same line of reasoning, Siarka (2021) propounded that since there are no industry standards, financial institutions are modelling RRs by implementing internal techniques designed with various assumptions. In practice, it is not an inconsequential matter to predict RRs since the empirical research work on RRs usually presents low model forecasting ability, and there is no industry accord on which model is best suitable for modelling bank loan RRs.

Several techniques have been implemented to examine RRs in several studies. These econometric methods offer insights into the potential predictor variables of RRs. In RR analysis, Siarka (2021) implemented Vasicek's one-factor model with the asset correlation parameter. Candian and Dmitriev (2020) implemented a dynamic stochastic general equilibrium technique to describe RRs variation, and Ye and Bellotti (2019) adopted a beta mixture technique combined with a linear regression with Lasso, logistic regression model, linear regression, inflated beta regression and beta regression to model RRs for non-performing loans. Kruger and Rosch (2017) implemented a quantile regression with exogenous and endogenous factors. They indicated that this regression technique outclasses the traditional regression and its modification with beta regression, regression trees, transformed response and mixture regression with two components. Min et al. (2020) applied exogenous and endogenous factors together with crisis forecasting to model individual RRs using several techniques. They compared regression models and their amalgamation with decision trees, neural networks and mixture models. Among all implemented techniques, Min et al. (2020) discovered that the mixture regression technique associated with regressed probabilities and regressed means of the components offers the best fit. For more expositions on RR models, see Bellotti et al. (2021), Nazemi et al. (2021), Chen et al. (2019a), Chen et al. (2019b), Toshiro et al. (2019), Khieu et al. (2012), Acharya et al. (2007), Altman et al. (2005), Dullmann and Trapp (2004), Chava et al. (2011) and Gupton and Stein (2002).

RRs of loans are usually bounded to the closed interval [0, 1] and have a bimodal distribution (Wang et al. 2020; Ye and Bellotti 2019; Yao et al. 2015; Dermine and De Carvalho 2006; Araten et al. 2004; Schuermann 2004b). Bimodality refers to a situation when RRs of loans are close to 100% (i.e., balance fully recovered) or 0% (i.e., no recovery or bankruptcy). RR modelling using parametric techniques has been a challenging exercise in academic literature and banking practice since RRs have unusual distributional characteristics. Consequently, several non-parametric models have been suggested to model RRs (Min et al. 2020; Starosta 2020; Sopitpongstorn et al. 2017; Loterman et al. 2012; Bastos 2010; Calabrese and Zenga 2010). Sopitpongstorn et al. (2021) implemented a non-parametric local logit model to describe RRs. In some cases, authors (see Min et al. 2020; Starosta 2020; Yao et al. 2017; Qi and Zhao 2011) indicated that non-parametric models are superior to parametric methods in modelling nonlinear associations between RRs and their covariates.

Even with the sophistication of the models designed to deal with bimodality, studies by Min et al. (2020), Starosta (2020), Li et al. (2016) and Qi and Zhao (2011) argued that these models do not necessarily provide better model fit than simpler models such as linear regressions and fractional regressions when applied to real LGD data. It has emerged that linear regression models can be compared with other sophisticated statistical models in terms of forecasting accuracies (Min et al. 2020; Bellotti and Crook 2012; Qi and Zhao 2011), even though there is a possibility of making predictions that are out of the range between 0 and 1 (Yao et al. 2015). In support of this, Hocht et al. (2022) exposed that the linear regression technique associated with a logarithmised response variable fits the aggregated RR best. Zhang and Thomas (2012) specified that linear regression techniques are superior to hazard models in some circumstances. For instance, the authors discovered that linear regression models have higher Spearman rank and R-square coefficients than hazard models in RR modelling. Evidence from Zhang and Thomas (2012) indicated that practitioners, regulators and academics do not need to apply the most complex parametric techniques to model RRs and LGD. Bellotti and Crook (2012) postulated that OLS techniques that incorporate macroeconomic factors perform superlatively in LGD prediction at portfolio and account stages on independent hold-out data matrices compared to a Tobit model, Beta distribution transformation, decision tree model and fractional logit transformation. Further, regression-type models are usually preferred in practice because they are flexible when modelling RRs. Ability, priorities and time restrictions are some of the reasons financial institutions employ regression-type models in RRs modelling.

3. Data and Methodology

3.1. Data

This study adopts a unique cross-sectional real-life data set of defaulted private non-financial firm bank loans gathered from a credit portfolio of a major anonymous Zimbabwean commercial bank over the sample period 2010–2018. The commercial bank of interest is one of the major commercial banks in Zimbabwe in terms of deposits, total assets and overall loans. Account default refers to a situation where a borrower is not likely to settle its debt commitments or more than 90 days past due on any substantial debt commitments (Basel Committee on Banking Supervision 2006). From this data set, we extract 14 predictor variables concerning firm characteristics and account features.

The preliminary sample has a total of 136 defaulted privately-owned non-financial corporation bank loans. State-owned, multinational and financial organisations that do not show the typical Zimbabwean private firms' real features are excluded from the sample. The bank loans are observed and traced annually, i.e., we employ annual data in this analysis. Loan accounts with financial statements that cover time horizons less than 12 months or that are recorded twice or more in the sample data or whose workout-processes have not been finalised are excluded from the sample. Facilities whose default amount is 0 are dropped as well. After data cleaning, 133 defaulted bank loans for 133 private non-financial firms pooled across the whole of Zimbabwe from diverse economic sectors remain in the final sample. Geographically, the data set is a true representation of the overall situation in the Zimbabwean economy. The whole data set is employed to fit the stepwise OLS models, i.e., the data set of interest is not segmented into training and validation data sets owing to its relatively restricted size resulting from fewer observations. Segmenting the data set into training and testing data sets may introduce bias (see Xu and Goodacre 2018). The data set meets the following conditions: (i) general mistakes are removed, (ii) default and payments data for all defaulted loans is available and reliable and (iii) the quantity of observations is sufficient to guarantee statistically significant in-sample results.

3.1.1. Recovery Rate Computation

Loterman (2013) and Basel Committee on Banking Supervision (2006) indicated that the three major components of the workout process are recoveries (cash or non-cash, i.e., collaterals), costs (direct or indirect) arising from the collection of recoveries, and the discount rate used on cash flows from the recovery process to express them in terms of monetary values at the default date. The data matrix used in this study comprises yearly cash inflows recovered by the bank after the default of the loans. That is to say, recoveries are in the form of annual summary. Cash inflows include payments made by customers and cash amounts realised from collateral. In practice, RR computation needs to incorporate material administration costs, whether direct or indirect, involved in executing and managing the workout process after loan account default. However, these costs are not considered in this research work since information about them for the data matrix adopted is not available. We compute the RR for each loan by discounting cash flows collected during the workout process to the date of default using the discount rate. RR refers to a portion of exposure recovered throughout the workout process, and its working definition is given by

$$\text{RR}= \frac{\text{Amount recovered or total repayments made over a period t after default}}{\text{Amount outstanding at default}} \quad (1)$$

Therefore, for each individual defaulted loan i, we compute RR rate using

$$\text{RR}_i= \frac{\text{Amount recovered}_\text{i}}{\text{Outstanding amount}_\text{i}} \quad (2)$$

Nevertheless, there is no harmony in the existent literature on which discount rate to use. In this study, the original contractual loan rate of interest is applied as the rate of discount. Chalupka and Kopecsni (2009) posited that the contractual loan rate of interest indicates the borrower's risk and opportunity cost of losing future payments.

RRs must be between 0 and 1. To fit the RRs in the interval [0, 1], the distribution of RRs is subjected to censoring. Some loans have negative RRs due to interests charged on them after default while firm borrowers are not paying anything. Hence, the outstanding balances keep on increasing. The RRs of these loans are pegged at 0. On the other hand, some loans have RRs that are more than 1. This happens when corporate borrowers settle the entire loan exposure at default plus interest and fees charged on them. The RRs for these loans are pegged at 1. Figure 1 is an empirical histogram that shows the RR distribution after censoring. The histogram is designed based on Equation (2) results for the 133 observations.

From Figure 1, we observe that the sample RRs are clustered close to 0% and 100%. The mean RR value is 0.61, the median RR value is 0.80 and the standard deviation is 0.41. Conceptually, the estimated RR is subtracted from 100% to get the workout LGD. The workout LGD is regarded as an essential element that financial institutions need to implement. Since 54.14% (72/133) of the sample RRs are at 0% and 100%, the results we get might be driven by these two extreme clusters. As a result, after we run models for the whole sample, we subdivide the sample into two sub-samples and then run the respective models for the designed sub-samples. The first sub-sample (sub-sample 1) is made up of the RRs for the two extreme clusters, i.e., RRs at 0 and 1, and the second sub-sample (sub-sample 2) is made up of the RRs in-between 0 and 1, i.e., RRs at 0.1–0.9.

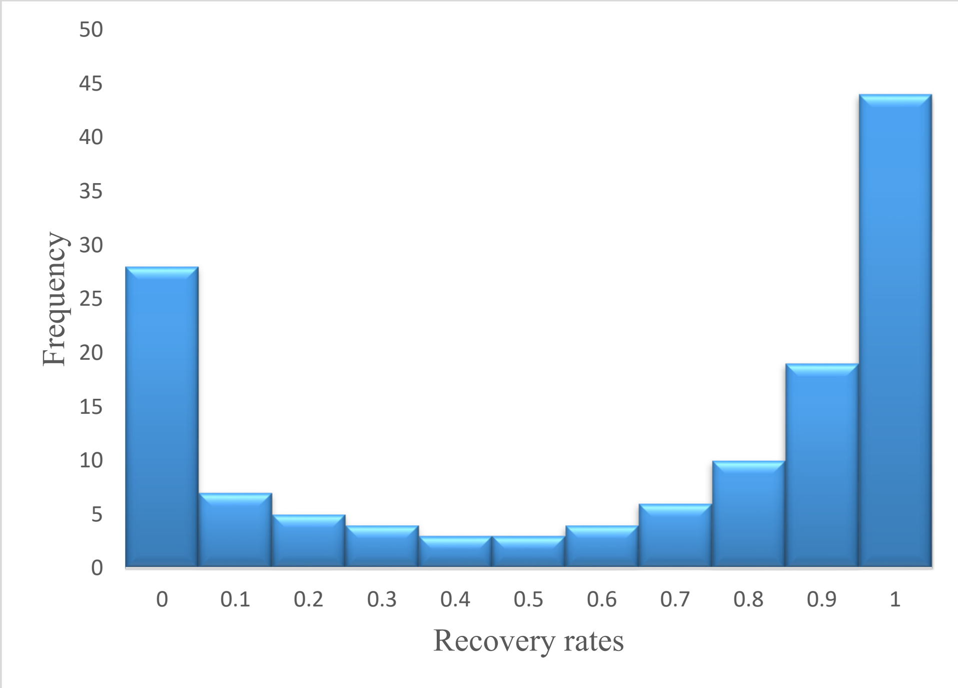

Figure 1. Recovery rate distribution.

3.1.2. Variables

In order to determine which drivers are related to the RRs for private non-financial corporate bank loans, the study concentrates on a set of determinants with firm characteristics, account features and macroeconomic variables (see Table 1). Considered in this analysis are RR drivers that are common in the extant literature, appropriate to the analysis at hand and have the superior predictive ability in empirical and theoretical studies. The study examines a set of financial statements filed exactly a year before default in compiling accounting ratios. Macroeconomic factors are extracted from the World Bank Group website, which is an online open-source. Table 1 also depicts the expected effects of candidate determinants on RRs. A positive (+) sign shows that an uptick in the value of the predictor results in a rise in the RR, while a negative (−) sign indicates a drop in the RR given a rise in the predictor's value.

Our sources of firm characteristics include information offered at the time of the application for loan and information provided 12 months before default. Firm age refers to the corporation's age from the day of its incorporation to the time of loan application. Time with the bank or length of business connection with the bank denotes the time the firm has been in a relationship with the bank. Number of creditors, which represent capital structure features, refers to the quantity of creditors the corporation has borrowed from at the time of application. Accounting ratios included in this article represent significant risk factors in RR analysis, i.e., size of the corporate, leverage, liquidity and profitability. The size of the corporate is given by the book value of total assets of the firm 12 months before default. We adopted the total debt/total assets ratio as a measure of leverage, the (current assets-current liabilities)/total assets ratio as a measure of liquidity and the ratio of earnings before interest and tax/total assets as a measure of profitability.

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

Abbreviation	Variable	Expected Effect
Panel A: Firm characteristics		
AG	Firm age	+
TwB	Time with the bank	−
TA	Total assets (firm size)	+
NC	Number of creditors	−
TD/TA	Total debt/total assets	−
(CA-CL)/TA	(Current assets-current liabilities)/total assets	+
EBIT/TA	Earnings before interest and tax/total assets	+
Panel B: Account features		
LAG	Age of loan at default	+
EAD	Exposure at default	−
LN	Loan amount	−
CLV	Collateral value	+
LwP	Length of the workout process	−
LMP	Loan maturity period	−
INT	Interest rate on loan	−
Panel C: Macroeconomic factors		
GNIC	Gross national income per capita growth	+
RGDP	Real GDP growth rate	+
INF	Inflation rate (% yearly average)	+
BB	Budget balance (% GDP)	−
PDE	Public debt (% GDP)	−
UR	Unemployment rate	−

Sources of loan or account features include information gathered at the time of application for the loan and information collected at the time of default. Including information pooled at the default time infers that the designed models are contingent on default. Although it is probable to develop RR models unconditionally, this is not in the scope of this research article. The sample consists of commercial bank (term) loans that disregard revolvers, bonds, or mortgage loans. Loan amount refers to the initial loan amount advanced to the firm at the time of application, while the interest rate is the original interest rate for the contractual loan. EAD is the total exposure a financial entity faces on a debt facility when a borrower defaults. The age of loan at default refers to the age, in years, of the loan from the opening date of the loan account to the default date. Collateral value designates the value of collateral pledged by the private firm borrower when given a loan. Collateral forms include land, equipment, residential real estate and commercial real estate but disregard personal guarantees. The workout process length is the period between the points of default and the final loss claim or write-off of the asset. In other words, the period of recovery begins when a borrower defaults or workout or collections department takes on a client's file and finishes when the file of the obligor is formally written-off or when the bank recuperates the amount owed and the debtor return to the active portfolio. Loan maturity period refers to the maturity period of the loan granted.

The RR and the PD have a negative relationship (see, for example, Rosche and Scheule 2011). Altman et al. (2004) argued that the PD may not be considered as a predictor variable when designing RR models because it is represented by the account-specific and firm-specific factors that are commonly applied when modelling PD and macroeconomic factors that can describe the common systematic risk to both RR and PD. Under the same line of reasoning, in this experiment, the PD is not incorporated as an explanatory variable since it is represented by the account-specific and firm-specific characteristics that are normally used when estimating PD and macroeconomic variables that can describe the common systematic risk to both PD and RR.

RRs are time dependent, i.e., they fluctuate over the business cycle. If the state of the economy changes, defaulters are affected in a number of ways. Consequently, in addition to firm and loan characteristics, we incorporate macroeconomic variables which act as proxies for macroeconomic conditions, i.e., gross national income per capita growth, real GDP growth rate, inflation rate (specified as a yearly average), budget balance (expressed as a percentage of GDP), public debt (stated as a percentage of GDP) and unemployment rate. Macroeconomic factors indicate the general condition of an economy. Our prior expectation is that as the gross national income per capita growth, real GDP growth rate and inflation rate rise, borrowers become more able to repay outstanding credit balances, thereby increasing the RRs. On the other hand, as the budget balance, public debt and unemployment rate increase, it becomes more difficult for obligors to pay off debts, thereby decreasing the RRs. In our study, we design and compare models with and without macroeconomic factors. If the model incorporating macroeconomic variables gives superior predictions than the model not including macroeconomic variables, we conclude that the included macroeconomic variables offer imperative information for the prediction of RRs.

To lessen bias and escalate precision, missing values are imputed instead of eliminating observations with missing data. Mean imputation is implemented since it is quick, not computationally challenging and it sustains sample size (Song and Shepperd 2007). In this technique, the average of non-missing values for each driver with missing value(s) is calculated. Each missing value is then replaced with the computed average. The firm's age and collateral value are each missing 0.75% of their values, translating into 1.5% of corporations with missing values. Outliers can substantially misrepresent the calculated model parameters and lead to incorrect inferences. To avoid the exclusion of the outliers from the sample data, extreme data points are winsorized at the distribution's 1st and 99th percentiles. Descriptive statistics for firm features, account characteristics and macroeconomic variables for the entire sample are computed. Moreover, given two extremely correlated RR determinants, one of them is excluded from the model(s) to deal with the multicollinearity problem since multicollinearity introduces bias in parameter estimates (Bade et al. 2011).

In this analysis, we implement two model structures founded on diverse combinations of predictor variables. These two model structures are subdivided into six models:

(i) Models based on firm characteristics and loan features.
- Model 1(a)—For the entire sample
- Model 1(b)—For sub-sample 1
- Model 1(c)—For sub-sample 2

(ii) Models based on firm characteristics, loan features and macroeconomic variables.
- Model 2(a)—For the entire sample
- Model 2(b)—For sub-sample 1
- Model 2(c)—For sub-sample 2

This study uses a stepwise selection technique with forward elimination to select the most statistically significant predictors at a 90% level of confidence. In stepwise selection, 0.15 and 0.20 are used as entry and removal probabilities, respectively, in order to include all relevant determinants of RRs (see, Hosmer and Lemeshow 2000).

3.2. Methodology

This sub-section gives a brief overview of the stepwise OLS regression model adopted in the study in order to examine RR drivers in the Zimbabwean private non-financial firm bank loan market. The RR of the defaulted loan i, RR_i, is given by

$$RR_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_n x_{ni} + \mu_i, \tag{3}$$

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

The workout LGD of the defaulted loan i, LGD_i, is then predicted in terms of RR_i

$$LGD_i = 1 - RR_i. \tag{4}$$

We adopt an OLS model because it offers several benefits. Collischon and Eberl (2020) and Verbeek (2017) opined that an OLS regression model presents the most comprehensible, natural and quick benchmark for other linear models and for more advanced techniques. Linear regression is the most obvious, popular and straightforward forecasting model to implement in the modelling of RRs and it can directly model recovery amount and recovery rate (Yao et al. 2015; Zhang and Thomas 2012). Further, Verbeek (2017) presented the following advantages of linear regression:

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

In reality, linear regression models are typically preferred because they are flexible when modelling RRs. Therefore, it is expected that OLS models can precisely describe the behaviour of RRs under distressed economic and financial conditions.

Unsurprisingly, the use of OLS models on censored RR data is associated with some challenges. If OLS techniques are implemented on censored RR data, the coefficients of regression can become biased (see, for instance, Amore and Murtinu 2019), since the distribution of censored RRs violates one of the typical assumptions of OLS regression, i.e., there is a random sampling of observations. Further, censoring removes vital variation of regressors but, in response, OLS regression techniques may not modify the estimates of coefficients so that they show the influence of censoring. Hence, OLS model results may become biased. To show the influence of censoring on model results, we run models for the entire sample, sub-sample 1 and sub-sample 2. Although the implementation of OLS models on censored RR data is linked with some challenges, in practice, OLS regression techniques are broadly implemented in examining censored RR distributions (see, for instance, Ye and Bellotti 2019; Bellotti and Crook 2012). Evidence from Min et al. (2020), Bellotti and Crook (2012) and Qi and Zhao (2011) indicated that linear regression models can be compared with other sophisticated statistical models in terms of forecasting accuracies. Hence, this piece of research work is comparable to other research articles.

To analyse and differentiate the in-sample predictive capacity of the developed RR models, our study uses the mean absolute error (MAE), root mean squared error (RMSE), Spearman's correlation coefficient (α) and coefficient of determination (R^2) (see Table 2). These performance metrics give the overall model fit indications based on the training sample. Each metric has its way of expressing the forecasting capability of the models in quantitative terms. The performance metrics measure either discrimination or calibration. Calibration shows how close to actual values are detected values, while discrimination implies the capacity to give a ranking of the response variable. The performance metrics' values are stated for comparative issues only. Consequently, this current study's devotion to the forecasting ability of the created techniques is restricted. Taking this into account, we therefore put our effort on identifying and interpreting the drivers of RRs for the defaulted private non-financial firm bank loans.

Table 2. Summary of the performance metrics for recovery rate models.

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

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

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

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

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

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

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

The Spearman's correlation coefficient ranks both actual and estimated values. It shows how accurate is the ranking of the estimated values. The Spearman's correlation coefficient is described by

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

where d_i indicates the variance between the ranks of forecasted and actual values. The Spearman's correlation coefficient assumes the values between +1 (indicating a perfect positive relationship) and -1 (showing a perfect negative relationship) with 0 indicating no relationship.

R^2 refers to a portion of described variance and is given by

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

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

4. Empirical Results and Analysis

Table A1 outlines the descriptive statistics for firm features, account characteristics and macroeconomic variables for the entire sample. Table A2 shows the correlation coefficients between the variables included in the designed models. Some of the variables are highly correlated, i.e., real GDP growth rate and gross national income per capita growth, inflation rate and gross national income per capita growth and public debt and unemployment rate. Hence, we drop public debt and gross national income per capita growth from the analysis since they are not widely used in the existing literature. The real GDP growth rate, the inflation rate and the unemployment rate are widely implemented in the extant RR literature and are associated with high predictive ability. From Table A2, we can conclude that the developed OLS models are not influenced by multicollinearity. We now interpret the determinants of RRs incorporated into the designed models.

4.1. Models with Firm Characteristics and Account Features

Table 3 below outlines the designed models based on firm and loan characteristics.

Table 3. Models based on firm and loan features.

Variable	Coeff. (p-Value)		
	Model 1(a)	**Model 1(b)**	**Model 1(c)**
Constant	0.143 (<0.001)	0.520 (<0.001)	0.133 (<0.001)
AG	0.146 (<0.001)		0.163 (0.038)
TA	0.012 (0.028)		0.032 (0.031)
EBIT/TA	0.153 (<0.001)	0.216 (0.046)	
(CA-CL)/TA	0.169 (<0.001)	0.206 (0.015)	0.246 (0.011)
TD/TA	−0.560 (<0.001)	−0.683 (0.044)	−0.511 (<0.001)
LN	−0.138 (<0.001)	−0.231 (<0.001)	
EAD	−0.025 (<0.001)	−0.087 (<0.001)	−0.040 (0.043)
CLV	0.039 (0.008)	0.250 (0.023)	0.184 (0.047)
NC	−0.019 (<0.001)		
LwP	−0.022 (<0.001)		
TwB		−0.099 (0.003)	
LAG		0.022 (0.005)	
LMP			−0.191 (0.027)
RMSE	0.2555	0.191	0.176
MAE	0.1410	0.127	0.116
R2	0.3348	0.387	0.428
α	0.5227	0.579	0.629

The experimental results of this study indicate that all covariates included in models 1(a)–(c) are significantly connected to the RRs for defaulted Zimbabwean private non-financial firm bank loans, with the total debt/total assets ratio, the EAD, the loan amount, the number of creditors, time with the bank, loan maturity period and the length of the workout process having a negative influence on the RRs, and the earnings before interest and tax/total assets ratio, the ratio of (current assets-current liabilities)/total assets, the age of the firm, the collateral value, age of loan at default and the total assets having a positive influence on the RRs.

We observe that the firm age has a positive association with the RRs, reflecting that established and mature firms are associated with high RRs while young and adolescent corporates are linked to low RRs. This is credited to the point that, compared to young and adolescent corporations, mature and established corporates have the experience, expertise and ability to effectively and efficiently deal with the recovery processes, thereby increasing the RRs. In support of this finding, Chalupka and Kopecsni (2009) and Dermine and De Carvalho (2006) posited that the firm's age positively influences the RRs. Conversely, Khieu et al. (2012) reported no association between RRs and the age of the firm.

The total assets book value, which is a proxy of corporate size, has a positive sign as expected, indicating that big firms are associated with high RRs and small corporations are characterised by low RRs. This proposition agrees with the research findings of Francois (2019) and Jacobs et al. (2010). Wang et al. (2020) found that huge corporates are characterised by improved RRs during good times. On the one hand, large, defaulted Zimbabwean privately owned non-financial firms are associated with high RRs due to the following reasons. They can efficiently and effectively steer a default and be transformed due to several aspects linked to size such as market power and government support. Moreover, they offer less severe information asymmetry difficulties to banks. As a result, their reorganisation procedures happen more rapidly than those for smaller firms. On the other hand, small Zimbabwean private corporations are more impacted by the domestic economy conditions compared to big firms and they lack the capability to service distressed loans, leading to low RRs. Contrastingly, Chalupka and Kopecsni (2009) proposed that if a huge firm defaults, several creditors compete for its assets, resulting in a low RR for the bank. Wang et al. (2020) articulated that huge corporations may be associated with greater bankruptcy costs, leading to lesser RRs especially under bad times. Moreover, Khieu et al. (2012) found no substantial association between RRs and the firm size.

We discover that the loan amount has a negative sign as expected, indicating that RRs decrease as the loan amounts increase. This shows that huge loans are associated with low RRs and small loans are linked to high RRs. Given that several recovery costs are semi-fixed, this finding is not surprising. Hence, the bigger the loan, the greater the recovery costs (making it difficult for firms to repay huge loans) and the lower the RRs. This finding is supported by Dermine and De Carvalho (2006) and Felsovalyi and Hurt (1998). Wang et al. (2020) highlighted that the loan size is negatively related to the RRs whether the credit cycle is good or bad. Further, Dermine and De Carvalho (2006) posited that usually a bank defers foreclosure on huge credit facilities since some bank customers who have business relations with a client with a huge loan in default would be negatively impacted by the foreclosure and end up in default on their loans as well. The authors (Dermine and De Carvalho 2006) promulgated that this potential "spill-over effect" leads to lower RRs when these huge credit facilities finally go in foreclosure. On the other hand, literature has indicated that financial institutions put more effort and resources into analysing the creditworthiness of borrowers with huge loans and monitoring them, resulting in higher RRs. Acharya et al. (2007) noted that the huge creditors' bargaining power may escalate RRs for enormous debts. Further, Khieu et al. (2012) and Thorburn (2000) reported that there is no relationship between RRs and the size of the debt facility.

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

The experimental outcomes reveal that the EAD has negative coefficients as expected, indicating that the greater the EAD, the lower the RRs. Fundamentally, the EAD indicates the proportion of the loan that is yet to be paid after default happens. It is essential to note that Zimbabwean privately-owned firms have been facing perennial viability problems for long. Consequently, huge outstanding loan balances are more challenging for the Zimbabwean private firm obligors to pay back under economic and financial stress. If a significant part of the borrowed amount is not repaid before the occurrence of default, the RR will be low and if a significant portion of the borrowed amount is reimbursed before the default, the RR will be great. This finding indicates that obligors with huge EAD expose the banks to more losses. Bellotti and Crook (2012), Bastos (2010), Chalupka and Kopecsni (2009) and Felsovalyi and Hurt (1998) supported this proposition. Nevertheless, this assertion is not consistent with the findings of Tanoue et al. (2017) and Tong et al. (2013).

Tanoue et al. (2017) suggested that the EAD positively influences the recovery probability, with a significant EAD resulting in a high recovery probability. A possible explanation for this is that banks strengthen their recovery efforts if the EAD is greater. Moreover, Tanoue et al. (2017) proposed that although a significant EAD results in a high recovery probability and makes the probability of incurring a loss low, obligors with huge EAD are likely to give rise to a loss.

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

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

The total debt/total assets ratio is a leverage indicator. Our study has a prior expectation of a negative sign for the total debt/total assets ratio's regression coefficients. This experiment discovers an inverse relationship between the private firm loan RRs and the ratio of total debt/total assets, indicating that as the ratio increases, RRs fall. This finding is not surprising since credit comes at a cost which adversely influences the capacity of firm borrowers to reimburse their loans. Since 2016, Zimbabwe has been experiencing chronic liquidity challenges and firms have been significantly using debt. The usage of high levels of leverage by private firms has weakened their cover against liquidity shocks, leading to low RRs. Francois (2019), Khieu et al. (2012), Carey and Gordy (2007), Acharya et al. (2007) and Varma and Cantor (2005) are some of the authors that exposed a negative association between the RRs and leverage. Acharya et al. (2007) articulated that corporations with greater leverage levels are connected to a higher scattering of debt ownership, which makes it difficult to hold talks regarding restructuring, thereby leading to low RRs. However, some studies discovered a positive correlation between RRs and leverage since firms with greater leverage levels are exposed to increased monitoring by banks, thereby increasing the RRs. Further, Wang et al. (2020) and Jankowitsch et al. (2014) found that leverage is not substantially linked to RRs.

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

The number of creditors, which is a proxy for the private corporates' capital structures, is negatively correlated with the RRs as expected, indicating that as the number of creditors increases, the RRs fall. Most Zimbabwean private corporations are often undercapitalised. Hence, they usually employ debt sourced from a number of creditors to finance their working capital needs and growth. Due to incessant viability challenges mainly caused by the existence of distressed financial and economic conditions, the majority of these private corporations have failed to pay-off their outstanding debts pooled from a number of creditors, leading to low RRs. Moreover, a challenging resolution process characterises private firms with several creditors as creditors compete for the corporations' assets, resulting in low RRs. In agreement with this assertion, Chalupka and Kopecsni (2009) discovered that a borrower with several loans is associated with a low RR.

In this study, we find that the time with the bank is negatively associated with the RRs, indicating that as the time with the bank increases, RRs fall, and as the time with the bank shortens, RRs increase. This sounds unreasonable considering that usually firm borrowers with long-term relationships with their banks enjoy a lot of benefits provided by their banks which include low interest rates and efficient monitoring. A possible explanation for this is that banks may not put extra effort and resources into monitoring and analysing the creditworthiness of borrowers with long-term relationships, leading to low RRs. Moreover, banks may be highly conflicted when dealing with defaulted customers associated with long-term relationships. Therefore, banks face risks for being reproached of abusing conflicts of interests or deserting their anticipated responsibilities as relationship banks, leading to low RRs. Our finding of the negative relationship between the time with the bank and RRs agrees with Zhang and Thomas (2012).

The age of loan at default is positively associated with the RRs, demonstrating that as the age of loan at default increases, RRs increase, and as the age of loan at default falls, RRs fall. If the loan defaults closer to its maturity date, a firm borrower can easily complete the debt repayments, therefore increasing the RR. The age of loan at default apprehend the propensity for loans associated with inferior quality to default sooner (Johnston-Ross and Shibut 2015). In support of our finding, Johnston-Ross and Shibut (2015) exposed that an upsurge in the age of the loan at default is related to an LGD decrease, indicating that an increase in the age of the loan at default lead to an increase in RR.

The study results reveal that the loan maturity period is negatively related to RRs, indicating that as the loan maturity period increases, the RRs drop, and as the loan maturity period shortens, the RRs surge up. This is not surprising since uncertainty increases with the maturity period of loans, which may increase the cost of long-term loans, among other things. For instance, European Commission (2005) articulated that interest rates for short-term loans are lesser than those for long-term loans due to lower uncertainty. In support of our findings, Zhang and Thomas (2012) and Kosak and Poljsak (2010) discovered an adverse relationship between loan term and RRs.

In terms of the prediction performance, model 1(c) is better than models 1(a) and 1(b) considering MAE, RMSE, R^2 and α estimates. Model 1(c) has the lowest MAE and RMSE values followed by model 1(b) and then model 1(a). Moreover, model 1(c) is associated with the highest R^2 and α estimates followed by model 1(b) and then model 1(a). Models 1(a)–(c) are capable of explaining 33.48%, 38.70% and 42.80%, respectively, of the variance in RRs. This indicates that models for the two sub-samples perform better than the model for the whole sample.

4.2. Models with Firm Features, Account Characteristics and Macroeconomic Variables

Table 4 below presents the developed models premised on firm features, loan characteristics and macroeconomic factors.

Table 4. Models premised on firm features, account characteristics and macroeconomic variables.

Variable	Coeff. (p-Value)		
	Model 2(a)	**Model 2(b)**	**Model 2(c)**
Constant	0.106 (<0.001)	0.216 (<0.001)	0.286 (<0.001)
TA	0.011 (0.032)		0.064 (0.034)
CLV	0.016 (0.003)	0.077 (<0.001)	
EAD	−0.041 (<0.001)	−0.096 (<0.044)	−0.054 (0.016)
(CA-CL)/TA	0.129 (0.004)	0.376 (<0.001)	0.294 (<0.001)
TD/TA	−0.174 (<0.001)	−0.280 (0.024)	−0.133 (<0.001)
LwP	−0.026 (0.028)		
EBIT/TA	0.109 (<0.001)	0.210 (0.019)	
INT	−0.139 (<0.001)	−0.255 (0.014)	
INF	0.100 (<0.001)	0.187 (0.028)	0.149 (0.002)
RGDP	0.115 (<0.001)	0.311 (<0.001)	0.132 (0.005)
NC		−0.078 (0.018)	
AG			0.052 (0.031)
TwB			−0.149 (0.026)
RMSE	0.2110	0.199	0.178
MAE	0.1164	0.108	0.009
R2	0.4249	0.461	0.506
α	0.6396	0.673	0.691

The empirical findings reveal that all explanatory factors included in models 2(a)–(c) are considerably correlated with the RRs for defaulted Zimbabwean privately owned non-financial firm bank loans, with the length of the workout process, the EAD, the total debt/total assets ratio, number of creditors, time with the bank and the interest rate having a negative influence on the RRs, and the total assets, the collateral value, the (current assets-current liabilities)/total assets ratio, the ratio of earnings before interest and tax/total assets, firm age, the inflation rate and the real GDP growth rate having a positive influence on the RRs. We observe that the signs for the estimated coefficients for the total debt/total assets ratio, the total assets, the EAD, the collateral value, the ratio of (current assets-current liabilities)/total assets, the earnings before interest and tax/total assets ratio, number of creditors, firm age and the length of the workout process are similar to those in models 1(a)–(c).

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

The study results confirm that macroeconomic variables influence the RRs as in the studies by Betz et al. (2018), European Banking Authority (2018), Bellotti and Crook (2012), Jacobs and Karagozoglu (2011) and Schuermann (2004b). However, Bijak and Thomas (2015), Calabrese (2014a), Gurtler and Hibbeln (2013) and Bastos (2010) renounced macroeconomic factors in their experiments. Some authors (see Brumma et al. 2014; Acharya et al. 2007; Dermine and De Carvalho 2006) analysed the univariate significance of macroeconomic variables which partially vanishes in a multivariate setting.

In particular, the real GDP growth rate enters models 2(a)–(c) with a positive sign as expected, indicating that as the real GDP growth rate increases, RRs rise. This discovered relationship is not surprising since a surge in the real GDP growth rate indicates that the economy is performing well and is moving in the right direction. The existent literature revealed that RRs are lesser in times of recessions and greater during expansions (see, for instance, Hanson and Schuermann 2004; Frye 2000). Under stressed economic and financial conditions, debtors are less likely to reimburse their debts, which adversely impacts RRs. Moreover, workout periods are lengthened during times of distress than during normal times (Shibut and Singer 2015), resulting in low RRs. In the same vein, Park and Bang (2014), Han and Jang (2013) and Khieu et al. (2012) discovered a substantial positive relationship between the RR and the real GDP growth. However, Wang et al. (2020) indicated that there is no association between the RRs and the annual GDP growth while Ingermann et al. (2016) observed that there is no significant association between RR and the real GDP growth.

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

Model 2(c) is better than models 2(a) and 2(b) in terms of performance considering MAE, RMSE, R2 and α values. Model 2(c) is associated with the lowest MAE and RMSE values followed by model 2(b) and then model 2(a). In addition, model 2(c) is associated with the highest R^2 and α values followed by model 2(b) and then model 2(a). Models 2(a)–(c) can describe 42.49%, 46.10% and 50.60%, respectively, of the variance in RRs. This shows that models for the two sub-samples perform better than the model for the whole sample.

Comparing RR models for each respective category, i.e., whole sample, sub-sample 1 and sub-sample 2, we observe that models with firm features, loan characteristics and macroeconomic variables describes RRs better than models with firm features and macroeconomic variables. Therefore, our study concludes that incorporating macroeconomic variables into the RR models gives a better model fit, resulting in substantial enhancement of the models' explanatory abilities.

Although the model fit is weak across all the developed models as indicated by R^2, such values are usual in RR modelling. The results found in this experiment are comparable to the results discovered in other studies such as Hocht et al. (2022), Ingermann et al. (2016) and Zhang and Thomas (2012). For example, using the training sample, Zhang and Thomas (2012) created a RR linear regression model and got an MSE of 0.1650, MAE of 0.3663, α of 0.3183 and R^2 of 0.1066.

5. Conclusions

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

In terms of performance, considering the models designed using the whole dataset, we reveal that the firm size, the collateral value, the exposure at default, the earnings before interest and tax/total assets ratio, the length of the workout process, the total debt/total assets ratio, the ratio of (current assets − current liabilities)/total assets, the inflation rate, the interest rate and the real gross domestic product growth rate are the significant determinants of RRs for Zimbabwean private non-financial firm bank loans. The results indicate that accounting information is useful in examining RRs for defaulted bank loans for private corporations under downturn conditions in Zimbabwe. This implies that financial statements are vital in predicting RRs for private non-financial firms under downturn conditions. Moreover, we discover that the prediction results of RR models are augmented by fusing firm features and loan characteristics with macroeconomic factors. The model (for the whole sample) founded on firm features and account characteristics has an R^2 of 33.48% and the model (for the whole sample) founded on firm features, account characteristics and macroeconomic variables has an R^2 of 42.49%. This implies that firm-features, account-characteristics and macroeconomic-information based RR models best describe RRs for private non-financial corporates under distressed conditions in a developing economy. In terms of comparison, the study shows that developed models for the two sub-samples perform better than the models for the whole sample. We recommend that loan features, firm characteristics and macroeconomic factors must be included when forecasting RRs for private corporates under stressed conditions.

In quantitative risk management, RR models back up the decision-making process of financial institutions, i.e., RR models are vital for financial institutions' risk-based decision-making. The designed RR models can be implemented in credit risk management and pricing. They can be implemented in the designing of collection policies to be implemented for defaulted firms, the formulation of credit terms, the determination of credit portfolios expected and unexpected losses and the computation of capital levels for loan portfolios. In modern-day banking and finance, the analysis of RRs has become an inescapable part of debt collection approaches in order to retain loans, on the banking books of financial institutions, that can be recovered and to write-off loans that are not anticipated to be recovered at an acceptable level. The examination of RRs assists financial institutions to fine-tune their debt collection strategies and the associated policies. Proposed RR models can help financial institutions in predicting downturn LGD and in stress testing. Debt recovery is also an imperative driver of the default risk premium needed by lenders. Conclusively, the envisioned use of the proposed RR models is to predict future RRs for capital requirement computations, enhanced risk assessment and improved bad debt management.

It is important to note that this current study has some limitations. The paper implements a restricted quantity of observations pooled from a single commercial bank in a developing economy. This may introduce some bias in the estimation of RRs. However, we assume that the results of this study can be generalised to other developing markets. For further research, this study may be improved in several dimensions. A vast sample dataset could be gathered over an elongated time period and applied in the analysis of RRs for defaulted private non-financial firm bank loans in order to augment the generalisability of the results. By increasing the dataset, further examinations on RRs' predictor variables for private firm defaulted bank loans under downturn conditions in developing countries can be done. A study that incorporates several parametric and nonparametric RR models can be performed in order to offer a better comprehension of any enhancements that can be attained over an OLS model. Although this study adopts a static model, it is well documented in the literature that RRs systematically differ through time. Thus, dynamic models that consider time-varying changes systematically in the RRs can be employed. Moreover, more appropriate predictor variables in a time variant framework can be combined to improve the models' prediction capacity. In reality, it is a usual thing to neglect the effect of censored RR data on the explanatory variables' coefficients. Nonetheless, the behaviour of censored RR distributions makes OLS regression techniques possibly unsuitable. Thus, to augment the prediction abilities of the models, techniques designed for censored data could be implemented in modelling censored RR data. Moreover, the study could be stretched to cover other financial instruments such as revolvers, mortgage loans and agricultural loans.

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Appendix A

Table A1. Firm characteristics, account features and macroeconomic factors with descriptive statistics.

Variable	Min.	Max.	Mean	SD
Panel A: Firm characteristics				
AG	2.00	85.00	25.72	23.33
TwB	1.00	21.00	6.45	4.63
TA *	3.13	212.37	33.95	54.29
NC	1.00	3.00	1.79	0.72
TD/TA	0.00	0.80	0.14	0.16
(CA-CL)/TA	−0.50	0.85	0.09	0.30
EBIT/TA	−0.51	0.36	0.04	0.14
Panel B: Account features				
LAG	1.00	4.00	1.43	0.63
EAD *	0.00	13.51	0.61	1.59
LS *	0.00	22.99	0.65	2.39
CLV *	0.00	19.03	1.87	3.71
LwP	1.00	7.00	2.82	1.46
LMP	1.00	6.00	2.47	1.15
INT	3.00	26.00	13.94	4.90
Panel C: Macroeconomic factors				
GNIC	−1.50	20.70	5.47	7.10
RGDP	0.70	19.70	5.60	6.63
INF	−2.40	10.60	0.93	2.98
BB	−11.20	−1.10	−4.10	3.86
PDE	37.10	54.20	43.76	6.37
UR	4.90	5.60	5.36	0.22

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

Table A2. Correlation coefficient matrix for recovery rate drivers incorporated into the models.

	TD/TA	EBIT/TA	TA	(CA-CL)/TA	INT	AG	CLV	EAD	LwP	NC	LN	RGDP	INF	TwB	LMP	LAG
TD/TA	1															
EBIT/TA	−0.21	1														
TA	0.10	−0.11	1													
(CA-CL)/TA	−0.15	0.19	−0.16	1												
INT	0.13	−0.26	−0.19	0.14	1											
AG	0.00	−0.10	0.50	0.03	−0.19	1										
CLV	−0.06	−0.04	−0.13	0.13	0.10	−0.05	1									
EAD	0.09	−0.10	−0.02	0.02	0.09	0.08	0.15	1								
LwP	0.05	−0.07	0.09	−0.01	0.01	0.14	0.12	0.10	1							
NC	0.12	−0.10	0.11	−0.13	0.03	0.03	0.10	−0.09	0.09	1						
LN	0.13	−0.01	−0.01	−0.01	0.08	−0.01	0.11	0.79	−0.01	−0.11	1					
RGDP	−0.16	0.06	0.09	0.04	−0.17	0.12	0.04	0.19	−0.14	0.06	0.19	1				
INF	−0.09	−0.13	0.19	−0.03	−0.19	0.09	0.01	0.09	−0.07	−0.02	0.09	0.53	1			
TwB	0.05	0.13	0.04	0.07	0.10	0.55	0.09	0.25	0.17	0.04	0.19	0.12	0.05	1		
LMP	−0.03	0.00	−0.07	0.06	0.06	0.20	0.08	0.15	0.14	0.11	0.16	0.09	0.02	0.54	1	
LAG	−0.14	0.01	−0.13	−0.10	0.11	−0.03	0.06	−0.02	−0.14	0.12	0.07	−0.19	−0.15	0.01	0.42	1

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