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Expected Loss Modelling in Banking Corporations in the Presence of Market Friction

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Abstract

Firms accounting for credit losses should undergo transition from estimation of incurred to expected loss models. New expected loss models must be motivated by concerns that reporting only incurred credit losses does not provide investors with sufficient information about banks' true credit risk levels. Based on risk metrics adjusted for market friction and fuzziness (vagueness or ambiguity), namely probability of default (PD), exposure at default (EAD) and loss given default (LGD), the research proposes an expected loss (EL) model for banks. We then proceed to validate the model using financial data drawn from listed banking corporations in Southern Africa.

Keywords: Credit losses; Expected loss models; Market friction; Fuzziness; Probability of default; Exposure at default; Loss given default; Vagueness; Ambiguity

Introduction

Credit risk models are considered to be direct applications of the frequency and severity of hazard rate models in financial organisations [1]. In modern financial world, structural and reduced form models represent two main categories of credit risk models. Structural form models aim to provide an explicit relationship between default risk and the capital structure of a firm. According to Reduced form models on the other hand are used for modelling credit defaults as exogenous events or variables. These models are driven by a stochastic process for example the Poisson jump process which is more realistic when it comes to returns to financial investments. Structural models by use modern option-pricing theory in the valuation of corporate debt [2,3]. The Merton model was the first structured model and serves as the cornerstone for all structural credit risk models. This paper was set out to investigate the impact of market friction on risk metrics of banks in Southern Africa in their desire to accurately measure expected losses and financial performance in their desire to grow and develop.

Background to the Study

Most banks in Southern Africa are characterized by the accumulation of non-performing wholesale and retail loans (NPLs) which have rendered their credit risk modelling and risk management policies and strategies ineffective. The above developments have seen most banks in the region being unable to meet their minimum capital requirements (MCRs), grow asset bases and shareholders' wealth, and face solvency and liquidity challenges and/or liquidation. It is therefore against the above background and challenges that this study is motivated to investigate the impact of the inclusion of market friction in credit risk models on bank financial performance in Southern Africa in their desire to grow and develop. Defines the concept of market friction as financial costs comprising transaction costs and taxes on capital gains [4]. He goes further to explain that market friction is not always a monetary cost as it includes incentives and commissions for agents and fees for brokers. In other words, the concept of market friction is taken to encompass costs of transacting financial operations such as capital and concentration charges, computers or machines, time-to-recovery and insider trading costs. The concept of market friction is extended to cover costs incurred by lending institutions from poor composition of banks' boards of directors (BODs), weak implementation of corporate governance, ethics and fraudulent transactions by loan officers and asset-liability committees (ALCOs). Market friction is therefore anything that prevents a financial transaction from being executed smoothly and transparently [5]. It can be taken to mean any reason which influences the process of decision-making of the investor in making financial transactions. Market friction can arise from misinformation about a financial product or the process of getting the exposure in the product, to the various legislative and legal hurdles and/or taxes levied on the transactions or any tedious and cumbersome activities that are likely to standing in a line to conduct a transaction, which might end up altering a preceding decision. Studied the effects of agency and information asymmetry issues on credit risk evaluation in American banks [6]. The study discovered that both caused significant deviations in credit risk evaluations of structural form models from agency ratings.

Argues that innovations in credit risk management and transfer were central if banks were to attain financial stability [7]. The above view in sync with works by also reiterated which concluded that lack of financial innovation and financial deepening seriously retarded growth and development of financial institutions. Total overhead costs are intimately related to market friction which the study seeks to factor into existing financial models to make them suitable to conditions existent in banks in emerging economies. Friction costs are the direct and indirect costs that are associated with execution of financial transactions, for instance, the fees and commissions along with total investments by banks. Macroeconomic factors (or system-wide variables) were identified as factors that cause banks' credit risk to rise [8]. Went further to note that the Central Bank's monetary policy can negatively impact on commercial banks' risk taking behaviour. The study found out that monetary authorities' austerity policies were stronger than expansionary policies and damaged the financial sector and commercial banks in particularly those in emerging countries. Direct transaction costs are total costs that financial borrowers incurred in the process of applying for a loan from a banking corporation. The costs included, for example, processing, insurance and additional costs that accrue on the loan obligation in the event of the failure of the borrower to settle both the principal and interest amounts as and when they fall due. Overheads, general and administration costs, are divided into two main categories of indirect costs that have a significant bearing on the financial growth and development of banking institutions in emerging economies. Hence this research study seeks to factor both direct and indirect transaction costs into existing credit risk models in its desire to accurately measure the financial performance of banks and similar financial institutions in developing countries. It has also been discovered that market friction is intimately related to corporate governance and economic rent particularly in developing countries. States that there are several theories that are concerned with financial sector problems, for instance the transaction costs and resource-based theories which focus on governance choice and economic rents respectively [9]. The transaction theories cited further to analyse market friction with respect to convergence and diversion of human factor, decision making, uncertainty and organizational factors, such as insider lending and their impact on overall performance of firms. The term economic rent is defined as the amount of money that the owner of land, labour or capital must receive in order to let someone else use the factor of production (FOP) respectively. Therefore, this research study was set to extend present-day financial credit risk models to include market friction which is not included in current models. Hence in the absence of market friction existing credit risk models become problematic to apply in estimation of risk metrics in most banks in developing countries. Market friction has been observed over time to be a real serious problem in most banks in developing countries that constrained their capacity to grow and develop. Most banks in Southern Africa are facing a multiplicity of challenges such as very high transaction costs that ranged from processing charges, commissions, interest obligations, low returns to savers, lending to connections and non-creditworthy borrowers to poor application of corporate governance and ethics.

Literature Review

Countries of the world use reduced and structural models in estimation of credit risk in banking institutions. Although these models are based on unrealistic assumptions such as constant risk free rates of return and constant asset volatilities they are acknowledged as the benchmark for valuation of assets and risk metrics of banks. Elizalde goes further to argue that reduced form models do not consider the link between default and firm value in an explicit manner in the modelling of credit risk. Reduced form models go further to specify recovery rates (RRs) after credit events have happened in banking corporations. However structural models on the other hand do not determine the time to default using the value of the firm, but take this variable to be an exogenous jump process parameter governing default hazard rate inferred from observable market data. Structural models are appraised for providing linkages between the credit quality of a firm and the economic and financial conditions it faces. Structural models do not specify RRs but provide values of assets and liabilities that are at default to be used in estimation of the recovery rates [10]. This flexibility in structural models suits very well the varied circumstances of banks in Southern Africa. Hence the expected loss model proposed by the study was derived from the structural models because of the robustness they contain in estimation of credit risk facing financial institutions. The current credit risk models used by international banks are based on the stipulations of the Basel Committee on Banking Supervision (BCBS, 2009)'s

Basel I, II and III Capital Accords. Internal-based rating (IRB) models, credit risk modelling may indeed result in better risk management systems [11]. The banks' IRB models can also be used in supervisory oversight frameworks of banking corporations including those in developing countries such as those in Southern Africa provided they are adjusted for market friction. Proposes a new model for the evaluation of capital charges for concentration of credit risk [12]. Kurtz's model holds when economic capital measurements are conducted within a multifactor framework [13]. The concept of concentration charge is defined through the impact of a particular sector on a portfolio's credit loss curve. One of the study's main propositions was that the Monte Carlo simulation should be used in credit risk modelling in banks. This is because the simulation does not require the calibration of additional parameters and hence was easily applicable to banks that performed simulations. Secondly, the simulation method has a tractable analytical formula that provides an efficient approximation because it is a simple or initiative location of the resultant capital charge. The study concluded that the simulation model was suitable for use in modelling capital charges for sector concentration risk under pillar II of the Basel II Capital Accord.

A recent study on credit risk proposes a new loss given default (LGD) model to address the missing and sample selectivity biases found in real life experiences [14]. Proposes a time to recovery survival model for the estimation of the LGD model with varying performance windows. Using an existing LGD data set, Chen performed five specification tests to evaluate the new approach to LGD modelling. The study realized that a trade LGD model (one that omits time to recovery and ignores censoring) was biased when applied to non-defaulted performing loans in which the time to recovery was unknown. This problem was addressed by proposing yet another new modelling approach. The approach entailed predicting both existing work out LGD data set comprising both censored and uncensored recoveries [15]. The model performed by Chen ensured that the new approximation model fitted data well resulting in a higher LGD prediction and marginal-sensitivity to triangles. It is important to note that a number of contemporary credit risk models and references therein, compete to explain the factors that impact on bank credit risk. The concept of bank credit losses is mainly influenced by three main traditional factors, namely PD, EAD and LGD. Developed a transaction cost model and realized that transaction costs were mainly influenced by the amount of loan applied for, real interest rates and land owned by the borrower [16]. He further argues that dummy variables such as collateral security, delinquency of the loan, Central Bank policies, the borrower's distance from the bank and the year in which the loan was borrowed are also part of the transaction costs. Banks needed good understanding of the link between solvency and funding risks to be able to assess their fragility efficiently and effectively [17]. Credit bubbles are becoming more common for several credit asset classes to which banks are exposed [18]. They proceed to argue further that credit bubbles have been observed to increase sharply with increases in corporate bonds and default on loans. It has also been observed that crises in credit and equity markets have contributed to periods of unfavourable price movements and increases in volatility in the above asset classes (before bursting of bubbles) and hence the need to manage the risks for growth and development of banking corporations. Most banks in Southern Africa have gone through a lot of changes and challenges in the 21st century whose impact on the financial sector cannot be quantified and compared with other emerging and stable economies of the world. For instance, Barclay's Bank Africa has recently been sold due to its failure to meet certain financial benchmarks that the shareholders were expecting over a long time period [19]. Therefore, a number of developing countries and those in Southern African countries in particular have financial sectors that have not adopted certain international banking standards for them to be globally recognized, efficient, stable, well-capitalized, competent and developmental. Hence wholesale credit risk models need to be developed that suit the regional countries' circumstances and capital bases in their quest to grow and develop.

Risk Metrics for the Proposed Model

This section discusses the approaches used in the estimation of risk metrics of banking corporations namely the PD, LGD, EAD using structural credit risk models. However structural credit risk models are based on assumptions of frictionless markets together with constant risk free rate of return and asset volatilities. These assumptions are far from explaining the reality found in financial markets in most emerging economies such as those in Southern Africa. Hence the research proposed and validated an EL model for implementation by banks in fuzzy financial markets characterised by market friction. As a market condition in which returns to financial market investments are not precisely defined as in probability theory but expressed in linguistic terms such as high, average or low [20]. This implies that the concept of fuzziness is intimately related to uncertainty as characterised by vagueness, generality and ambiguity. Fuzziness is founded on the principle of continuous variables in the range (0;1) and not exactness or discrete variables as under structural credit risk models. The study calculated three market friction adjusted risk metrics namely PD, EAD and LGD required in the estimating of ELs of banks in fuzzy financial markets. Therefore fuzziness does not have a well-defined set of bounds and is not resolvable with specific reference to context as opposed to the other terms. The other terms vagueness, generality and ambiguity can be contextually eliminated and conclusions that are closely linked to investors' language judgements can be made. It is a fact that integral applications that combine linguistic variables and pragmatism are more powerful and beneficial to individual investors and firms and hence the need for new credit risk models that suit in a given financial market conditions facing most banks in emerging economies.

Approach to estimation of the PD

The fundamental accounting equation of a firm is given by

$$A = E+L, \qquad (1)$$

Where A is total assets, E is total equity and L is total liabilities. The first theorist to transform the option pricing model into a valuation model for estimation of firms'assets and risk metrics. Although the Black-Scholes option pricing model was so flexible in application, it was founded on unrealistic assumptions that necessitated the need to extend structural models to capture market friction and uncertainty. The research therefore extended the structural PD model to the case for inclusion of market friction and uncertainty in valuation of PDs of banks in emerging economies. A firm defaults on its obligations when its assets are less than its liabilities. This is because its Equity will be negative, which can be given away at zero cost. Structural form models are also known as firm-value models. Acknowledges that the liabilities of a firm consist of one zero coupon bond with notional value, L maturing at time, T and will have no payments until, T at which default decision is taken. The PD is defined as the probability that the value of a firm's assets, A< L, its liabilities, at time, T. The probability distribution of a firm's assets at time, it is developed on the assumption that the firm's assets follow a lognormal distribution [21]. The logarithm of the assets of a firm follows a normal distribution (ND) at T. In other words once the mean and variance of the credit exposures of a firm have been estimated, its risk metrics such as expected loss (EL) can then be calculated. Uses the Black-Scholes model to model the default behaviour in a financial organization. The study combines structural and reduced form models in order to come up with a hybrid PD model for banks in emerging economies. Reduced form models are based on credit spreads on non-defaulted risky bonds or loans trading on markets currently. Spreads that lie above treasury bonds for instance are an indicator of risk premiums that are demanded by investors. Such spreads, spreads normally reflect ELs including PDs, LGDs and liquidity premiums [22-25]. The study sought to extend the existing structural credit risk model for PD to include a market friction component. Therefore the famous Merton's asset valuation model (AVM) that was extended to the case for market friction in this study was premised on two simultaneous linear equations founded on the assumption that firms' asset values and volatilities, VA and σA are unknown. The two equations for estimation of firms' asset values and standard deviations if not known are as outlined below. Market Value of Equity is given by,

$$VE = VA \times N(d_1) - \quad \times Xt \times N(d_2) \qquad s \qquad (2)$$

The volatility of equity of a firm is given by,
The standard deviation of equity,

$$\sigma E = \frac{VA}{VE} \times N(d1)\sigma A; \qquad (3)$$

However for the research at hand firms' asset values were given in their financial statements and only asset volatilities were calculated. The research extended the Merton's structural PD model,

$$PD = \frac{N[ln\left(\frac{VA}{Xt}\right)+(r-\frac{\sigma_A^2}{2})T]}{\sigma_A\sqrt{T}} \qquad (4)$$

To the case for a PD model adjusted for market friction given by the general form,

$$PD = \frac{N[ln\left(\frac{VA}{Xt}\right)+(\mu RE-\mu CE+\frac{\sigma_A^2}{2})T]}{\sigma_A\sqrt{T}} \qquad (5)$$

Where; VA=Value of firm's Assets and VE=Value of the Firm's Equity, T=The tenure of the asset, µRE =The return on ordinary equity, µCE = The cost of ordinary equity (Market friction).

On the other hand $N(d_1)$= The cumulative normal probability distribution of the Z-Score, d_1 and $N(d_2)$=The cumulative normal probability distribution of the Z-Score, d_2.

The extension of the structural PD model was reached in the desire to make the model suitable to the financial circumstances of banks in developing regions such as Southern Africa.

The estimation of the EAD

This is the amount that a bank is expected to lose in the event that the obligor will default on a loan obligation. According to the Bank for International Settlements (BIS) and Basel Committee on Banking Supervision (BCBS, 2009), EAD must not be lower than the book value of the Statement of financial position (SFP or balance sheet) receivables and should be calculated at the facility level. The EAD of a firm can be based on lines of credit or derivatives that is vanilla and on the counter (OTC) instruments or depending on movements of certain asset classes. The methods to be used in the modelling of credit derivatives include current exposure methods (CEM), standardized methods (SM) and internal model method (IMM). However under the internal ratings based approach (IRB), EAD can be calculated using the Foundation approach (F-IRB) based on lines of credit and off-balance sheet (OBS) transactions. The traditional EAD is calculated using credit conversion factors (CCF) that are provided for in the Basel guidelines excluding collaterals and guarantees or securities. On the other hand the EAD of a firm can also be estimated using the advanced approach (A-IRB) which allow banks to use own models. In other words A-IRBs accord banks the flexibility to generate or select models for use in calculating their EADs. Under the CCFs, the amounts owed by borrowers to the bank at time T =EADs. These can either be fixed or variable exposures. Fixed exposures are exposures that banks have not made commitments to provide credit in the future and on-balance sheet (OBS) values such that EAD=Drawn Credit Lines that is EAD =The Current Amount Outstanding on a firm's balance sheet and hence no modelling is required for Basel II Requirements. On the other hand variable exposures are exposures under which banks will provide future commitments on in addition to the current credits that is such exposures have both on and off BS values.

In other words the firm's EAD was estimated in this study using the formula,

$$\text{EAD} = [\text{Drawn Credit Lines} + \text{CCF}\times \text{Undrawn Credit Lines}](1-\text{MF}), \quad (6)$$

Where

$$\text{CCF} = \frac{\text{Increase in Exposure Until Default Day}}{\text{Maximum Possible Increas in Exposure Until Default Day.}} \quad (7)$$

And MF is market friction or costs of issuing loans in this case.

Calculated CCFs must be checked for appropriateness for current macroeconomic scenarios before being used in the calculation of EADs of firms. The study at hand intends to adjust the above EAD model for market friction for instance corporate governance costs to enhance its robust in estimation of EADs for banks in Southern Africa where markets are highly frictional, unlike the case in developed countries.

The formula for calculation of LGD

A bank is said to have incurred a loss when a company to which it has lent out money defaults on its principal and interest obligations. According to the Bank for International Settlement (BIS, 2018), default on a credit exposure is said to have occurred when one or more of the following events have taken place.

- The obligor is past due more than 90 days on a credit obligation.
- The obligor has filed for bankruptcy or similar protection from creditors and
- The LGD is the percentage loss rate on the EAD given the obligor's defaults.

The actual loss incurred by the bank=LGD× EAD. The components of loss to be incurred by the bank are the loss of the principal, carrying costs and workout expenses. It should however be noted that firms' LGD values are known for varying with economic cycles namely cyclical LGDs (Point in time LGDs), long run LGDs (Throughout the cycle LGDs) and downturn LGDs. Cyclical LGDs are based on recent data and depend on economic cycles while long term LGDs are average long term LGDs corresponding to noncyclical variables that do not depend on the time at which the LGDs are calculated. Downturn LGDs represent the LGDs of firms at the worst time of the economic cycle, say at the lowest peak of a recession. The Basel II Framework (See BCBS, 2009) requires that LGDs of firms must reflect downturn conditions wherever it is necessary to capture relevant risks facing the organization. It is also recommended that banks should use downturn LGDs when credit losses for given asset classes are expected to be higher than the averages. Therefore under the F-IRB approach, senior claims on sovereigns, corporates and banks that are not secured by acceptable collaterals are given higher LGD values of 45% and subordinated claims are given LGD values of 75%.

Under the A-IRB approaches, LGDs should be estimated using any of the following internal rating methods.

- The market LGD, based on market values of defaulted bonds or loans.
- Workout LGD, based on cash flows from a firm's workout processes.
- Implied LGD, based on the market prices of non-defaulted bonds or loans and
- Statistical LGD, based on regression techniques on LGDs and facility characteristics for example qualitative forms of market friction such as spreads and macroeconomic environment.

It can be argued that of the four LGD methods above only market and implied LGDs approaches are less computation intensive and normally work well for liquid financial market instruments. Banks are therefore advised to use market or implied LGD approaches to estimate their LGDs under the above conditions and employ workout LGD methods when they hold illiquid and non-marketable instruments, which is usually the case in most emerging economies. However under conditions of large exposures, banks should apply techniques that make it possible to estimate more precise LGDs. For forecasting of LGDs statistical LGD methods should be used as long as it is possible to establish dependent and independent linear relationships. The LGD under the workout approach is estimated from the equation,

$$\text{LGD} = \frac{\text{EAD}_\text{T} - \text{PV}[\sum \text{R}_\text{t}) + \text{PV}(\sum \text{C}_\text{t})}{\text{EAD}_\text{T}}, \quad (8)$$

Where

PV (R_t) and PV (C_t) are recoveries and costs incurred during workout prices and processes respectively.

The implied LGD approaches are based on observed market information such as stock prices and hence the use for instance of the Merton model, as specified in this study. On the other hand statistical LGD approaches stipulate that a firm's LGD lies between values of 0 and 1. Hence the study estimated banks' LGDs model after transforming banks' LGDs into a variable,

$$\text{X}_\text{t} = Log\,\frac{LGD}{1-LGD} \quad (9)$$

To suit into the current family of logit or logistic models where,

$$X_t.= \alpha_0 + \alpha_1 y_1 + \alpha_2 y_2 + \cdots \ldots \ldots \ldots \ldots \ldots \ldots + \alpha_n y_n \quad (10)$$

The above logistic model for LGD estimation is applicable when,

- Only significant variables are incorporated into the model.

- The variables used have economic meaning in explaining the variability in firms' LGDs.
- Independent variables are able to explain the LGDs significantly and
- The financial data collected should be properly processed leaving out all outliers.

Table 1: *Logit Model Statistical Measures (Results) for Bank B (2008-2013).*

Financial Ratio	Coeff	Std Error	t-Value	P> (t)	95% CI
PD	8.76e-09	7.56e-10	-0.96	0.648	-4.24e-10 3.71e-09
EAD/TA	7.20e-09	6.80e-10	-0.75	0.732	-3.64e-10 4.48e-09
LGD/TA	5.92e-09	4.84e-10	-0.68	0.896	-2.82e-10 3.32e-09
MR	4.68e-09	3.62e-10	-0.42	0.585	-1.42e-09 3.32e-09
Cons	28.72				

Table 2: *Logit Model Statistical Measures (Results) for Bank B (2008-2013).*

Financial Ratio	Odds Ratio	Std Error	t-Value	P> (t)	95% CI
PD	1	6.42e-10	-0.86	0.586	1 1
EAD/TA	1	6.60e-10	-0.75	0.632	1 1
LGD/TA	1	4.86e-10	-0.40	0.795	1 1
MR	1	5.92e-10	0.26	0.835	1 1

Table 3: *Logit Model Statistical Measures (Results) for Bank S (2008-2013).*

Financial Ratio	Coeff	Std Error	t-Value	P> (t)	95% CI
PD	9.60e-08	8.54e-09	-0.64	0.705	-4.48e-09 1.43e-09
EAD/TA	8.60e-08	6.91e-09	0.59	0.676	-3.63e-09 2.18e-09
LGD/TA	7.24e-08	5.65e-09	0.54	0.624	-2.54e-09 3.28e-09
MR	6.55e-08	3.80e-09	0.48	0.646	-1.48e-09 8.58e-09
Cons	48.75				

Table 4: *Logistic Model Statistical Measures (Results) for Bank S (2008-2013).*

Financial Ratio	Odds Ratio	Std Error	t-Value	P> (t)	95% CI
PD	1	8.98e-09	-0.56	0.672	1 1
EAD/TA	1	7.84e-09	0.60	0.568	1 1
LGD/TA	1	6.48e-09	0.53	0.586	1 1
MR	1	4.58e-09	0.48	0.646	1 1

Proposed model for estimation of ELs of banks

After estimation of all the three risk metrics above, ELs
Of banks can be evaluated under a true reflection of the actual market circumstances faced in developing countries such as those in Southern Africa. The study therefore proposed an expected loss (EL) model for banks' exposures, given by,

$$EL = PD \times EAD \times LGD, \qquad (11)$$

Where all the independent variables are market friction adjusted parameters. A model of this nature suits very well the fuzzy or uncertain nature of human behaviour when it comes to making planning and decision making processes in financial markets.

Model Validation, Results and Discussion

The model proposed above is validated using financial data drawn from two large listed banking corporations obtained from emerging economies in Southern Africa. The study used logit/logistic to come up with results for the expected loss (EL) values of the two large banks drawn using convenience sampling. The two banks were targeted mainly because they were listed on stable and prudentially regulated Stock Exchanges in the region under investigation. The logit or logistic linear regression models are mainly used in research studies for predicting dichotomous outcomes such as in events that result in success and/or failure outcomes or possibilities. However the model is frequently used because it is so flexible that it can also be used to predict odds dependent variables from quantitative continuous random variables. The majority of dependent variables of interest to researchers such as expected loss suit well for dichotomous analyses and interpretations. Therefore, logistic regression is a standardised statistical package that can be likened to other world-wide popular packages such as SAS, STATA, SPSS, R and E-Views. The logit model is a binary model in which the dependent variable, Y is a binary response to X is any type of covariate or independent variable, which is either dichotomous or continuous variable. In this case X assumes three fuzzy independent variables, namely PD, EAD and LGD which are adjusted for market friction, cost of capital in particular. The exponential linear regression model, also called the logit model is a function of fuzzy variables above given by,

$$Y = e^{\sigma+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\beta_n MF}, \quad (12)$$

Where MF=market friction, represented by the cost of capital or equity of a firm. When the above logit model is transformed into a multiple linear model using logarithmic form it becomes a logistic regression model of the form,

$$\text{Log}\left(\frac{\text{EL}}{\text{NEL}}\right) = \sigma+\beta_1 X_1 + \beta_2 X_2 + -------- + \beta(n-1)\ X\_(n-1) + \beta\_n\ MF \quad (13)$$

Where EL= Probability of expected loss from a corporate borrower and NEL= Non-probability of expected loss. The Xs are covariates or predictor variables, σ and βs are logistic regression coefficients to be estimated from given odds and predictor values. The term in the brackets on the left hand side is called the odds, calculated as the probability of the success event divided by the event of no success. The logarithmic term of the odds is a linear function of the covariates given on the right hand side. The study used the STATA package to analyse the two banks' audited financial statements for the period 208-2013. The study regressed log odds of the banks over the period under review with three risk metrics namely PD, EAD and LGD as the independent variables. The independent variables were expressed as percentages of total assets of the bank in order to make the findings comparable. The STATA package was used mainly because of its strength of having two commands namely the logit model (where expected loss output could be used to generate coefficients) and logistic model (where expected loss output data gave rise to odds ratios) for use in analysing audited financial research data for banks.

Distribution of bank B's logit model results (2008-2013)

The bank's logit regression model for the period under consideration was based on 36 observations and 16 replications. The following results were attained using jack-knife approach (running logit on estimation sample data) for analysis and interpretation of research data:

The F statistic, F(1, 15) = 4.54 and Log likelihood = 0 and Prob > F = 0.05.

The equation connecting the variables is given by the formula, Y(log odds)=28.72 +8.76e-09PD+ 7.20e-09EAD/TA + 5,92e-09LGD/TA+4.68e-09MF. The study therefore discovered that the expected loss of a bank was directly related to PD variable, EAD and LGD ratios to total assets of the corporation. Overall the bank's expected loss depicted a weak positive relationship with market friction over the period 2008-2013. The logit model's 95% confidence intervals for the variables' betas fell in the range -4.24e-10 to 4.48e-09 (which lay between the discrete bounds -1 and 1). The above results implied that the expected loss for the bank was around 0.00 for the period under investigation. Hence the corporate's expected loss on loans issued were very small but meaningful. Therefore credit exposures that the bank issued in the period performed fairly well. This may be attributed to the fact that the bank's risk management models and strategies used were more effective and well managed to see it grow and develop in its loaning business.

Distribution of bank b's logistic model results (2008-2013)

The 95% confidence intervals for the betas in the logistic model contained the bound 1. This implied that the probability of default had no significant association with all independent variables drawn into the model. The t-statistic values for all betas of variables in the model were less than 0.50. This finding suggested that the model could be very reliable in predicting the expected loss for the bank for the period under investigation. However odds ratios of value 1 as shown in the table above meant that in reality the default event occurred in the bank in the 2008-13 and was related to all independent variables drawn into the model including market friction.

Logit model statistical measures (results) for bank's (2008-13)

The logit regression model used 36 observations with 16 replications to analyse the bank's financial data for the period under investigation. The study came up with the following results, F statistic, F(1, 15) = 4.54 and Log likelihood = 0 and Prob > F =0.05.

The STATA package used came up with 0 failures and there were 36 completely determined successes. The logit model connecting the variables above was of the specific form, Y(log odds) =48.75 +9.60e-08PD+ 8.60e-08EAD/TA + 7.24e-08LGD/TA+ 6.55e-08MF. The logit model therefore revealed that the bank's expected loss increased as PD and market friction increased. Furthermore the study discovered that the bank's expected loss depicted a positive relationship with EAD/TA and LGD/TA ratios for the period 2008-2013. The 95% confidence intervals for the betas of the variables fell in the range, -4.48e-09 to 8.58e-09, which fell in the discrete bounds of -1 and 1. The above research finding implied that the expected loss for the bank's corporate credit exposures were clustered around 0.00 for the period in question. Hence the company's expected loss on all loans issued were overall smaller compared with those of bank B. Therefore the credit exposures that the bank issued to corporates though smaller than those issued by the other bank performed fairly well in the period 2008-2013. It was revealed in the study that bank S had more consumer than corporate loans as compared to bank B which concentrated on corporate loans alone in the period under review.

Distribution of bank s's logistic model results (2008-13)

The 95% confidence intervals for betas of bank S's financial data in the logistic model contained the bound 1.00 coming in as both lower and upper bounds were 1s. However the intervals implied that the bank's expected losses had no significant association with all variables drawn into the model. The t-distribution values for all betas of variables incorporated in the model were less than 0.50. This suggested that the model could be very reliable in predicting the expected loss of the bank for the period under consideration. On the other hand odds values of 1.00 across all independent variables reflected that expected loss had occurred in bank S's corporate lending activities in the period under investigation. However since the percentages of expected loss to total assets, PD, EAD, LGD and market friction of the bank were relatively low, it could be deduced that the bank's corporate credit risk management models or strategies used were efficient and effective. The 95% confidence intervals for the betas of covariates in the model contain the bound 1 which revealed that the expected loss had no significant association with all independent variables analysed. However the t-distribution values for all betas of independent variables had values less than 0.50. This suggested that the model was fairly reliable in predicting the expected loss for the bank for the period under review (Tables 1-4).

Conclusions and Recommendations

The study proposed and validated a market friction adjusted expected loss model in order give a true reflection of the characteristics of financial markets in emerging economies. The study used logit and logistic valuation models to analyse financial data drawn from audited financial statements of banks for the period 2008-13. Market friction and uncertainty were added to the model in order to increase the precision or exactness required in valuation of firms' exposures in emerging financial markets. The study therefore concluded that banks in emerging economies operated in uncertain financial markets characterised by friction, volatile interest and asset values. It was also concluded that efficient estimation of ELs was achieved through inclusion of mathematical languages or human behaviours and non-quantitative variables contrary to notions of the classical probability theory used in structural models. The adjustment of existing structural credit risk models for market friction created the rigour needed in the estimation of both asset and EL values of firms in emerging economies. Expected loss models that were adjusted for market friction fairly reflected the firms' actual market values and risk metrics. This development was likely to go a long way in assisting banks in their planning and management of corporate loans, loan loss provisioning and decision-making processes. The study also concluded that expected losses of both firms had an indirect relationship with their PD, EAD and LGD variables. Furthermore, the study concluded that banks drawn from the region were poorly capitalized, measured in terms of the ration of ordinary equity capital compared to debt financing. The banks over-depended on borrowed capital in their capitalization which rendered them vulnerable to hostile takeovers by the providers of such capital in the foreseeable future. However since banks were able to turn both equity and debt finance into assets it implies that they were somehow hedged against hostile takeovers by bondholders. Shareholders of banks in the region needed to inject adequate equity capital into their banks to be able to grab their ownership and improve financial performance, asset accumulation and shareholders' wealth from the debt-equity funders. Alternatively they could negotiate with existing lenders for converting their over-borrowed statuses into equity to reduce the banks' indebtedness and increase issued share capital. This strategy had the ability to reduce their exposure to interest and principal loan obligations. The study finally concluded that banks in emerging and frictional financial markets need new look expected loss models in order to be efficient in valuation of risk metrics and EL in particular. Expected loss models adjusted for market friction, uncertainty and human perceptions or uncertainty were more realistic, precise and practical compared to the structural and reduced-form models premised on assumptions of frictionless markets. New models to be used in estimating risk metrics must shift from estimation of incurred to expected losses. The expected loss models to be adopted and implemented by banks in emerging markets must be motivated by human perceptions that reporting only incurred credit losses will not provide investors with sufficient information about their true credit risk levels and metrics.

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Based on the above conclusions premised on frictional financial markets, the study recommends that banks in emerging economies need to urgently come up with well formulated, coordinated and prudentially implemented financial policies and strategies in order to effectively manage their capital challenges, credit exposures, expected losses and finance their development processes through mainly equity capital. These policies and strategies were to go a long way in the betterment of banks' fortunes in terms of their regulation and supervision, capital injection and let alone effective issuing and management of their credit exposures in frictional financial markets. The study also recommends that banks must improve their assets' income generation power to enhance effectiveness in management of their loan exposures, financial obligations, both long and short term liabilities and accumulation of assets and generation of wealth for the shareholders. The study went further to recommend that banks' boards of directors (BODs) and senior management should be re-oriented so that they shift from estimation of firm values and risk metrics using structural models. Extending current structural models to inclusion of market friction in firm valuation was not only critical but improved their precision and rigour. Factors such as perceptions of investors or shareholders, market friction and uncertainty should be included in estimation of firms' equities, assets and expected losses valuation models to improve practicability and reliability of their overall financial performance, growth and development processes. Therefore overall the study recommends that banks in emerging frictional markets can adopt and implement the proposed expected loss model as a more realistic and reflective models compared to structural models that suited frictionless markets that existed mostly in developed countries of the world. The model at hand suits very well the financial circumstances of banks such as those in Southern Africa because it was robust and sensitive to the impact of both market friction and uncertainty on the fair valuation of banks' asset, equity and expected losses.

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