Journal of Banking and Finance Management
Volume 2, Issue 1, 2019, PP 43-59

Analysis of the Stochastic Approach to Debt Management in the Banking Sector in Nigeria

Frank Alaba Ogedengbe (Phd)

Department Of Business Administration , Michael And Cecilia Ibru University, Delta State, Nigeria

***Corresponding Author:** Frank Alaba Ogedengbe (Phd), Department Of Business Administration, Michael And Cecilia Ibru University, Delta State, Nigeria, Email: ogendengbefrank@mciu.edu.ng*

ABSTRACT

This research focuses on stochastic approach to debt management in the banking sector in Nigeria. The aim was to identify the methods adopted by banks in managing debt and to ascertain the adequacy of these methods in debt management as well as investigate the superiority of the Markov chain approach over other methods. Convenience sampling was adopted to select one of the twenty four banking institutions in Nigeria. Secondary data were collected and analysed using the prudential guidelines and the Markov chain for comparison purpose. The results revealed that the banks do not entirely follow the parameters in the cannons of lending in their credit creation process. Banks rely solely on prudential guideline in managing debt. This has not drastically reduced the proportion of non-performing loans in the sector. The study demonstrated the superiority of the stochastic method of debt management over the prudential guideline or the traditional method of debt management. This is shown by the drastic reduction in the proportion of non-performing loans written off, a situation that has the capacity of leading to a higher profit margin when compared with reliance on the prudential guidelines method of debt management.

INTRODUCTION

It is a common reality today that large proportions of commercial transactions are carried out on credit basis. This situation is not limited to the developed economies of the world as it is also noticeable in the developing economies. This credit basis of business transactions has compelled managers in organisations to be concerned with the acquisition of skills required to efficiently manage this large volume of accounts receivable. In managing these credits, managers have adopted different valuation methods of accounts receivable. In a bid to ensure uniformity in operations, banks regulatory agency provided debt management guidelines. Despite this regulatory provisions, the proportion of nonperforming loans and advances increases on annual basis. It is a global fact that financial institutions are confronted by difficulties over the years for a myriad of reasons. One of the most serious banking problems continue to be directly related to lax credit standards for borrowers and counterparties. Others include but not limited to poor portfolio risk management and insensitivity to changes in economic variable of the customer and other circumstances, that can lead to deterioration in the credit standing of a bank's counterparties. This experience is common in both developed and developing economies of the world. We earnestly subscribe to the position that the continuous reliance on the provisions of the CBN prudential guidelines will increase the large amount annually written off of the accounts receivables of banks in Nigeria. We hereby advocate the usage of Markov process a stochastic model as another estimation technique for approximating the proportion of the accounts receivable that will go bad or be written off each period in Nigerian banks. Markov chain is a special class of stochastic process that is suitable for characterizing a good number of banking operations particularly, those relating to debt management. A typical situation involves accounts receivable and the proportion of it that will go bad in a period under review (Cyert, Davidson & Thompson, 1962; Olonisakin, 1992; Thomas, 2000; Budnick, Mc Leavey & Mojena, 2004; Kama, Adigun, & Adegbe, 2013). The stochastic characteristic of credit, accounts receivable and bad debts are evident from the difficulty to accurately tell which c facilities will become unpaid or which will fail when granting credit to customers..

A failed credit is a bad debt and a loss to the organization. Often, we are faced with decisions of uncertainty, such as granting of facilities which include loans, overdrafts and other advances, credit sales, movement of stock prices, machine performance, personnel and manpower management, weather forecast and customers' patronage or brand switching. Bad debt is an expense charge against the organization's revenue. It has the tendency of eroding the profit of the organization and hence, the need for prudent management of accounts receivable and debts (Welch, 1962; Cyert, Davidson & Thompson, 1962; Agbadudu, 1996). According to CBN (2010, p.8), "banks review their credit portfolio continuously with a view to recognizing any deterioration in credit quality. Such reviews, systematically and realistically classify banks' credit exposure based on perceived risks of default.

The assessment of risk of default is based on criteria which include, but not limited to, repayment performance, borrowers' repayment capacity on the basis of current financial condition and net realizable value of collateral. Credit facilities are classified as either performing or non-performing. A credit facility is deemed to be performing, if payments of both principal and interest are up to date in accordance with agreed terms." A credit facility is deemed non-performing when interest or principal is due and unpaid for a period of over 90 days (CBN, 2010). As lofty as these assessment criteria are, they fail to consider a crucial factor, the willingness of the borrower to repay both the sum borrowed and the accrued interest. Willingness itself may be characterised by other factors which are extraneous, or otherwise, in nature, to the borrower.

This may be the bane of the high rate of bad debt and the failure rate witnessed in the sector recently. Various methods of determining, estimating and making provision for doubtful accounts abound. This is firstly, to classify the accounts into age categories, show the stages and ages of accounts delinquency. The second involves the application of the loss expectancy rates, which currently are judgment estimates of the proportion of the debt liable to become uncollectible. The loss expectancy rates are policy parameters based on past experience, firms' expectation of economic conditions, firms' conservation in financial policy and other similar factors. The stochastic and random nature of credit, accounts receivable and bad debt are not considered. Also, a common feature of these processes or methods is that only one value is estimated for bad debt (Cyert, Davidson & Thompson, 1962; Lanzennauer & Wright, 1975).

Literature Review

Accounts Receivable

Accounts receivable according to Welch (1962), is a legally enforceable claim for payment to a business by its customers and clients for goods supplied, services rendered or facility granted in execution of the customer's order. Accounts receivable management is a vital function performed by financial managers. This function requires the manager to monitor and follow up on outstanding accounts. The financial stability of an organization is dependent on the effective and efficient monitoring of positive cash flow. It is expedient that an organization maintain a steady flow of income and revenue to cover expenses required in order to meet the organization's objectives. The primary objective of accounts receivable management is to minimize the amount of time that accounts are outstanding. Outstanding accounts are the accounts that are due to be repaid by the customers but have not been able to make any payments. This demand that accounts receivable management involve tracking the amount that have not been paid, assessing actions required to secure payments and implementing procedure to secure payments.

Credit Creation And Management

Traditionally, the banking industry is known for its intermediation role in providing financial assistance needed in the economy. This role is normally carried out via granting of loans, overdrafts and other advances to customers, which constitute the major part of banks' lending. Apart from loans and overdrafts, there are other forms of bank credits or bonds issued by banks for and on behalf of customers. Lending is one of the major functions of banks, though the most risky. Yet any bank that wants to remain in business must lend. Due to the fact that banks' primary function is to act as intermediary between savers and borrowers, the barometer for measuring their earnings is interest from lending.

Credit Creation

Creation of credits, which are in the form of loans, overdrafts and advances, are the total amount of money a given bank lends out to its customers at any given period of time. Thus banks usually charge the borrower interest for using its money. These loans and advances usually have maturity period. In providing credits for business ventures, banks should, as a matter of importance, take all necessary steps to ensure that advances are granted to those customers who can and will make judicious use of loans so that repayment will not become a problem. Therefore, credits must be made to people who are capable of utilizing it properly and repaying the loan at its maturity.

The place of loans and advances in the affairs of banks can be explained by referring to the fact that "loans and advances are the largest single item in the assets structures of Nigerian Banks'' (Ani, 2012). It also constitutes the main source of the operating income of banks and also the most profitable assets for the employment of banks' funds (Kama, Adigun, & Adegbe, 2013; Olonisakin, 1992; Nwankwo, 1999).

The Role Of Banks In Credit Creation

Banks are traditionally seen as financial intermediaries. They have been seen as financial intermediaries that channel deposits to those who want to borrow. It is still acknowledged that banks can "create credit". Credit creation in the traditional context is defined as the process by which saving is channelled to alternative uses and hence banks are mere financial intermediaries. The understanding of banks is that they gain their profits from borrowing short-term and lending long-term by the extension of loans. Banks create credit and money out of thin air.

However, the reality looks different. If a bank extends a loan, it does not even need the object it wants to lend out, it can simply create it out of nothing. Therefore, banks do not lend money, they create it. It is crucial to understand that credit creation by banks is not simply the transfer of existing purchasing power, where banks would be mere intermediaries, but they create new purchasing power (Nwankwo, 1999). It is believed that the Holy Grail of economics is to understand the role of credit creation. Jhingan (2002), states that the main business of banks is to extend loans, the borrower receives a fictitious deposit receipt or deposit entry in his bank account, although no deposit had been made. Banks create credit, they do not lend money.

Banks create the bulk of all money in the economy by pretending that a borrower has deposited money. However, this system can only work as long as others accept the pretended money. Banks simultaneously create credit and money. Thus, banks themselves create the deposits, not the customer. In the view of Ezekiel (1997), banks are legally required to keep a fixed percentage of their deposits in cash and then, lend or invest the remaining amount. It is the amount lent that actually leads to the credit creation process.

Credit Management

After credit creation by banks, they are left with the responsibility to ensure that these loans are repaid as at when due. To be able to manage the credit properly, they are classified as short term, medium/long term and contingent credit.

Short Term: The short term credit is a facility granted to customers that are usually repayable within a year and is in most times in the form of an overdraft.

Medium/Long Term:This refers to a credit that is payable over a period of more than a year. A medium term facility could be repayable between one to five years whereas long term credit falls within ten years and above. An example of this class of credit is a mortgage loan.

Contingent credit arises from certain event which occurrence cannot be guaranteed by special credit. This is a type of credit that is customized to meet specific needs of bank clientele.

It is important to state that, before a loan facility is granted by a financial institution, certain criteria must be fulfilled. These criteria are often refereed as the 'Cannons of credit or cannons of lending'. These cannons of lending are presented below;

- **Capital**: Basically, capital is the equity that a firm has which upon liquidation of the firm will be available for debt repayment, if all other means fail. It equally represents the borrower's stake in the company. Consideration is given by the financial institutions to whether the company is sufficiently capitalized for the business it is involved in and that for which the loan is being requested.
- **Character**: This refers to the borrowers reputation and hence desire to settle debt obligation.
- **Collateral**: This acts as the backup plan if the first sources of repayment fail to pay back the loan. Normally, banks do not wish to exploit this option as it usually involves a

lot of paper and legal work. The collateral could be in the form of landed property, stocks and shares in blue chip companies and any other source that is acceptable to the bank.

- **Condition**: This refers to the environment under which the business operates. Economic conditions affect the ability of the borrower to repay financial obligations. These economic conditions are beyond the control of the borrower and the banker.
- **Capacity/Cash flow**: This entails ensuring that the borrower has the legal and economic capacity to borrow. This implies that consideration is given to projected cash inflow and outflow of the customer. Certain pertinent questions need to be answered. Such questions include; is the business able to generate adequate cash inflow after cash outflows are taken care of to repay the loan?

  To be able to achieve this, The "Basel committee" recommends that "banks need to understand to whom they are granting credit. Therefore, prior to entering into any new credit relationship, a bank must become familiar with the borrower or counterparty and be confident that they are dealing with an individual or organization of sound repute and creditworthiness. In particular, strict policies must be in place to avoid association with individuals involved in fraudulent activities and other crimes. This can be achieved through a number of ways, including asking for references from known parties, accessing credit registries, and becoming familiar with individuals responsible for managing a company and checking their personal references and financial condition. However, a bank should not grant credit simply because the borrower or counterparty is familiar to the bank or is perceived to be highly reputable."
- **Consideration**: This refers to other factors that are likely to prop up during the credit approval process. Factors such as obligator's limit and composition of the lending banks portfolio come under other consideration.

Doubtful And Bad Debts

Doubtful debts are those debts which a business or individual is unlikely to be able to collect. When there is no longer any doubt that a debt is uncollectible, the debt becomes bad. Once accounts receivable or a doubtful account becomes uncollectable, the amount will be written off depending on accounting conventions, regulatory framework and the institution's provisioning (Welch, 1962; ECOA, 1976, CBN, 2010). Bank loans in the USA, according to Welch (1962) and (ECOA, 1976), with more than ninety day's arrears become "problem loans". Accounting authorities in Nigeria and the central bank of Nigeria's prudential guidelines for money deposit banks in Nigeria advise that the full amount of a bad debt be written off to the profit and loss account or a provision for bad debt as soon as it is foreseen (CBN, 2010).

Causes Of Bad And Doubtful Debts

The causes of bad debts are less obvious than they always seem. First and foremost is that it could result from no or delayed payment of interest and or principal for a given period. The most obvious causes of loan repayment default, especially in a depressed economy, can be seen in the readiness of the bank to give increasing volume to an applicant. Thus resulting in a situation of the more one borrows, the more one would want to borrow. Consequently, this increase in the volume of the loan would decrease the ability to repay as opposed to the willingness to repay. The ability to repay increases with increased net income, although that does not say anything about the willingness to repay. One would expect borrowers with high net income to have low debt or equity ratio. The implication is that the lower the debt or equity ratio, the higher the ability to repay (Olonisakin, 1992; Agu, & Okoli, 2013 and Kama, Adigun & Adegbe, 2013).

In a similar vein, Onwudiegwu (2001) posits that, as the value of the collateral increases, the default rate is expected to decline. Where there is income variance as a result of economic or natural circumstances, credit service ability per individual borrower decreases and hence default could increase. Another cause of loan default is high interest rate. The higher the interest rate, the more the outstanding balance the borrowers have to pay, considering the principal. It is pertinent to acknowledge that the rate of inflation has link with the real interest payable by the borrowers. If inflation is higher than the interest rate, it will mean that the lending bank would be paying borrowers to take its loans. Another notable cause of bad debt is inadequate monitoring of borrowers with the aim to ensure a loan is not diverted to unproductive use. This exercise though costly, has a lot of bearing on ability of the borrower to repay, and consequently, avoiding a situation that could result in doubtful and bad debt (Olonisakin, 1992; Agu, & Okoli, 2013 and Kama, Adigun, & Adegbe, 2013).

Concept of Credit Scoring

Credit scoring is a method of evaluating the credit risk of loan applications. This entails using historical data and statistical techniques. Credit scoring tries to isolate the effects of various applicant characteristics on delinquencies and defaults. The outcome of the process is a “score” that a bank can use to rank its loan applicants or borrowers in terms of risk. Essentially, credit scores are numbers generated by a computer program that reads through all credit reports. It looks for patterns, characteristics, and ‘tell’ tale signs in applicant’s records. On the basis of this, the program spits out a credit score for the loan applicant (Thomas, 2000; Malik & Thomas, 2009).Credit scoring is essentially a way of recognizing the different groups in a population when one cannot see the characteristic that separates the groups but only related ones. It is about discriminating among groups in a population. One could use the same techniques to discriminate among good and bad loans. Decisions on whether to give loans or send merchandise had been made judgmentally by credit analysts for many years. Hitherto, credit analysts apply the rules of thumb when making decisions on whom to give loans. These rules were then used by non-experts to help make credit decisions in yester years (Fisher, 1936; Durand, 1941; Johnson, 1992; Thomas, 2000).

Numerous events showed the benefits of statistically derived models in lending decisions. The arrival of credit cards in the late 1960s made the banks and other credit cards issuers realize the usefulness of credit scoring. The number of people applying for credit cards each day made it impossible both in economic and manpower terms to do anything but automate the lending decision. The argument according to Capon (1982) was the brute force empiricism of credit scoring offends against the traditions of society and that there should be more dependence on credit history. This could possibly explain why certain characteristics are needed in a scoring system and others are not. According to Batt and Fowkes (1972), credit scoring systems are statistically-based tools for forecasting the outcome of extending credit to individuals and organizations. This scoring system attempts to distinguish between potentially good and bad credits. This suggests that credit scoring system facilitates a structured approach to spotting potential credit problems early enough and thereafter institute appropriate remedial actions. The characteristics that enable the organization to discriminate between good and bad debt best are derivable statistically. These characteristics are then attended with in terms of maximum scores depending on the degree with which they discriminate between these two states. Cut off points totals are thereafter established between the potentially good and bad debts. This implies that scoring schemes are usually designed so that high scores indicate high risk of default and low rates indicate low risk of default. It is pertinent to remark that these characteristics used for scoring differ from firm to firm and depend on the types of facility (Cyert, Davidson, & Thompson, 1962; Batt & Fowkes, 1972; Thomas, 2000).In addition to the computer programming technique of generating customers’ credit scores, Logistic Regression and Linear Programming are currently being applied. These two techniques were later introduced. Artificial Intelligence techniques like Expert Systems and Neural Network are the most recent additions. Now the emphasis is on changing the objectives from trying to maximize the chance a customer will default on one particular product to looking at how the firm can maximize the profit it can make from that customer. Moreover, the original idea of estimating the risk of defaulting has been augmented by scorecards which estimate response, usage, and retention, attrition and debt management (Cyert, Davidson, & Thompson, 1962; Thomas, 2000; Malik & Thomas, 2010).

Credit Scoring Method

This is the traditional method employed by financial institutions in managing outstanding debts. This, in essence, is relying on subjective analysis which has some important limitations. However, Thomas (2000) observes that “loan officers differ in their experience and in their views regarding the relationships between risk and specific credit characteristics of applicants. Consequently, an institution cannot be sure that its underwriters are approving all applications that have risk profiles consistent with the objectives of the institution. In addition, because of the numerous and often complex factors mortgage underwriters need to consider, subjective underwriting is time-consuming and costly."

Malik and Thomas (2010) further opined that "to facilitate the mortgage underwriting process, reduce costs, and promote consistency, credit scoring models have been developed that numerically weigh or score some or all of the factors considered in the underwriting process and provide an indication of the relative risk posed by each application. In principle, a well-constructed credit scoring system holds the promise of increasing the speed, accuracy, and consistency of the credit evaluation process, while reducing costs. Thus, credit scoring can reduce risk by helping lenders weed out applicants posing excessive risk and can also increase the volume of loans by better identifying creditworthy applicants"

Generically, scoring is a process that uses recorded information about individuals and their loan requests to predict, in a quantifiable and consistent manner, their future performance regarding debt repayment.

Scores represent the estimated relationship between information obtained from credit bureau reports or loan applications and the likelihood of poor loan performance, most often measured as delinquency or default. Scoring has been used to assess applications for motor vehicle loans, credit cards, and other types of consumer credit for decades (Thomas, 2000).

Regulatory Framework

The Central Bank of Nigeria's (CBN) Prudential Guidelines for deposit money banks in Nigeria (2010), provide that banks should review their credit portfolio continuously, at least once quarterly.

This is to classify systematically and realistically banks' credit exposure based on perceived risk of default. Such assessments are based on criteria that include but not restricted to, repayment performance, borrowers' repayment capacity and net realizable value of collateral. Prior to the introduction of banks prudential guidelines, most banks believed that once loans or overdrafts were secured, whether the accounts were serviced or not, interest on it should continue to be credited to their profit and loss accounts believing that they would realize the security in case of default in payment. Most often banks were not too bothered as to whether the collateral was perfected or not thereby making realize ability of collaterals difficult, if not out rightly impossible.

The guidelines also made allowance for non performing loans in order to reflect their true financial condition. Credit facility is deemed non-performing, if either the principal or interest is due and unpaid for 90 days or more and or rolled over into a new loan. Furthermore, non-performing credit facilities are classified into sub-standard, doubtful and lost. Sub-standard facility is one which unpaid principal or interest remains outstanding for more than 90 days but less than 180 days. Facility is doubtful, if principal and or interest are unpaid for at least 180 days but less than 360 days. Facility on which principal and or interest remain outstanding for 360 or more days and are not secured by legal title to leased assets or perfected realizable collateral in the course of collections or realization is deemed lost (CBN, 2010).Specific provisions are to be made on the basis of perceived risk of default on specific credit facilities while general provisions are expected to be made in recognition of the fact that even performing credit facility harbours some risk of loss no matter how small. The guidelines also aver that Credit facility is deemed to be performing if the payments of both principal and interest are up-to-date in accordance with the agreed terms. Banks are required to make adequate provisions for perceived losses in the following ways. Facilities classified as Sub-standard, Doubtful and Lost, principal and or interest overdue by more than 90 days should be fully provided for and suspended as the case may be and recognized on cash basis only. Whereas for principal repayment not yet due on non-performing facilities, provision should be made as follow:

Sub-standard credit facilities 10%of the outstanding balance

Doubtful credit facilities 50% of the outstanding balance

Lost credit facilities 100% of the outstanding balance

However, the Non-performing Loans (NPL) of a bank should not exceed 50% of its total loans disbursed to its customers (CBN, 2010).

Modern Methods of Credit Management

Credit scoring nowadays is based on statistical or operational research methods. The statistical tools include discriminant analysis, which is essentially linear regression. Variants of these are logistic regression and classification trees, sometimes called recursive partitioning algorithms. Most scorecard builders use one of these techniques or a combination of the techniques. Credit scoring also lends itself to a number of different non-parametric statistical and Artificial Intelligence modelling approaches. Another notable statistical technique suitable for ascertaining the proportion of loan repayment that can become delinquent is the Markov chain (Thomas, 2009).

In life, business and management, we are often faced with making decisions based on phenomena that have uncertainty associated with them. Processes that evolve over time in a probabilistic manner are called stochastic processes. One of such is accounts receivable and what proportion of it that will go bad in a period under review. Markov process describes the dynamics of a system. Specifically, it describes movement among the different states of the system as a function of time. Movement of people, inventories and money have been described as Markov processes. Some situation involves an evolutionary process. The system starts with a set of initial conditions. Then certain changes develop in the conditions, eventually, the system evolves into a stable pattern. The Markov process has been successfully applied in sundry fields, disciplines, endeavours and issues, both locally and internationally and bothering on a wide range of differing topics, subjects and discourses. Issues like probability for start of rains and annual rainfall distribution for crop production (Stern, 1981; Yusuf, Adamu, & Abdullahi, 2014),assessment of students' admission and academic performance (Adeleke, Oguntuase, & Ogunsakin, 2014), cooking fuel usage (Adamu & Danbaba, 2014), assets returns prediction (Raheem & Ezepue, 2015), dynamics of vehicular traffics (Olaleye, Sowunmi, Abiola, Salako & Eleyoowo, 2009) and the management of both local and foreign debt (Olonisakin, 1992; Ngaloru, Abdulazeez, Ebuk, Adiukwu & Nafiu, 2015).

Other areas where the Markov process has been applied with high level of accuracy, efficiency and effectiveness include, forecasting risks in lending to customers (Thomas, 2000), modelling credit risk in portfolios of consumers loans (Malik & Thomas, 2000), forecasting and predicting bad debt and future bad debt losses for a given portfolio of accounts receivable (Lanzenauer& Right, 1975), facies model determination (Ikoro, Amajor, Inyang, Okereke, Ekeocha, Ibeneme, Israel, Nwagbara & Essien, 2014), accident analysis (Igboanugo, 2010), brand switching (Ehrenberg, 1965), modelling customers relationships (Pfeifer & Carraway, 2000) and analysis of manpower data (Igboanugo, 2011).Still other areas where the Markov process has gained acceptance, popularity and credibility include prospect of stocks and stock market forecasting (Idolor, 2011; Preethi & Santhi, 2012), stock market price trends and behaviour (Zhang & Zhang, 2009; Eriki & Idolor, 2010; Landauskas & Valakevicius, 2011; Prakash & Arora, 2012; Zhou, 2014; Zhou, 2015; Bairagi & Kakaty, 2015), analyzing child mortality (Adebayo & Fahrmeir, 2002) and corporate manpower planning (Igboanugo, 2013). In the case of forecasting and predicting bad debt and future bad debt losses for a given portfolio of accounts receivable, there are instances where a system enters into one or more states from which once there, it cannot exit to other states. A company needs to keep track of the money that it is owed from its customers as well as from other companies. This is a case of Account Receivable. The individual accounts could be classified into states, which definitely will include paid and bad debt. Once a debt is paid, it cannot be in bad debt or in any other state at that. The same happens, if the amount or account becomes bad, a state that the debt cannot be recovered or repaid by the debtor. These state (paid and bad states), are known as Absorbing States. Once the system is in any of these states, it cannot exit into some other states in the system (Doob, 1953; Dasgupta, Papadimitriou, Vazirami & David, (2009).If it is possible to move from one state to the other in a system without any encumbrances, that is, no state in the system where once entered cannot be exited, a time will come when the system will be in a stable or steady state. On the other hand, there exist in some system no steady or stable states, because there are absorbing states in such systems. The case on hand, the account receivable example, has no steady state instead it has absorbing states, the paid and bad states (Dasgupta, Papadimitiou, Vazirani, & David, 2009; Doob, 1953).

Markov Process: Cyert, Davidson & Thompson, 1962; (Cdt Model)

In the Cyert, Davidson & Thompson (1962) **CDT** model, the "Total Balance Method" of aging is used. This requires a sharp distinction to be made between total balance age and the real age of the account. CDT developed their model in terms of the total balance method and used it to estimate the real age of the distribution of the accounts receivable. Following the CDT balance method, the age of account can be defined as the age of its latest or oldest loan repayment. This implies assigning the balance of all accounts into transit age categories as paid bad debt absorbing states. They describe the movement of an account by the age it has at time t and by that it has at time t+1.Various methods are being currently employed in managing information about accounts receivable, provision for bad debt and bad debt losses. In the most simplistic procedures, these bad debt losses are estimated by multiplying a historically experienced loss ratio with some quality such as account receivable. Other procedures take the age of the account receivable into consideration and use age related ratio to determine loss expectancy rate and make provision for bad debt losses (Welsh, Zlakkovich & White, 1972, Lanzenauer & Write, 1975). In the Nigeria banking sector, the prudential guideline provision is the standard for the estimated and provision for bad debt in particular as the management of credit in general (CBN 2010).

METHODOLOGY

This section examines the research design adopted for this study, the sources of data, the population and sampling method. It also discusses model formulation and the data estimation technique. The research design adopted in this study is survey. This is premised on Agbonifoh and Yomere (1999) assertion, that any study that focuses on the sampling of individual units of a population is survey in nature. The central theme of this study is loan disbursement and credit management in the Nigerian banking industry. This implies that the study examines the quarterly loan repayment policies and practices of Union Bank credit management data between 2009 and 2014 the extreme years inclusive within a time frame of five years. Primary and secondary data were employed in this study. The primary data was sourced using questionnaire from the present credit managers of the bank's regional office, while the secondary data were sourced from the annualized published data of the bank. The population of study is the entire twenty-four, banking institutions in Nigeria. To determine the sample size of study convenient sampling method was adopted. This decision is premised on the ease of accessibility and the willingness of the management to cooperate with the researcher and in addition to the fact that the same central bank's prudential guidelines govern all money deposit banks operations in Nigeria.

MODEL SPECIFICATION

The strategy here is to use the Cyert, Davidson and Thompson (**CDT**) 1962 model for this research. If we consider the balance of accounts receivable at time ***i*,** the balance can be classified then, or at any subsequent time into each of ***n*** age categories (Cyert, Davidson, & Thompson, 1962). Suppose for a balance of receivable at time ***i*,** we let

$\mathbf{B_o}$ = Credit (Debt) 0 period (or payments) past due (current)

$\mathbf{B_1}$= Credit (Debt) 1 periods (or payments) past due

$\mathbf{B_j}$= Credit (Debt) j periods (or payments) past due

$\mathbf{B_n}$= Credit (Debt) 1 periods (or payments) past due

Consider now a balance of accounts receivable as of time ***i*** at the next later time period **i+1.** At time **i+1**, the balance at time ***i*** can be classified in two ways, according to the age category where it is now. Let $\mathbf{B_{jk}}$ be the balance of category **k** at time **i+1** which came from category **j** at time ***i*.** **B** can be an **(n+2)** square matrix where individual entries $\mathbf{B_{jk}}$, balance in category **j** at time ***i*** moves to category **k** at time **i+1.**

$$\mathbf{B} = \begin{matrix} B_{\ddot{o}o} \dots B_{\ddot{o}x} \dots B_{\ddot{o}n} \\ B_{j\ddot{o}} \dots B_{jk} \dots B_{in} \\ B_{n\ddot{o}} \dots B_{nk} \dots B_{nn} \end{matrix} \qquad 1$$

From the **n+2**matrix of balance **B,** an **n+2** matrix of transition probabilities **P** can be de eloped. The transition probability $\mathbf{P_{jk}}$, will be defined as the probability of debt in classification **j** at time ***i***transiting to classification k at time **i+1**. In terms of $\mathbf{B_{jk}}$, $\mathbf{P_{jk}}$can then be defined as.

$$\mathbf{P_{jk}} = \frac{\mathbf{B_{jk}}}{\mathbf{\Sigma B_{jk} = 1, j = 1, \dots, N}} \qquad 2$$

The following can also be computed:

$$\mathbf{A = b\,[\pi NR - (\pi NR)_{sq}]} \qquad 3$$

$$\mathbf{V = c[\eta N - \Sigma\, ({}_{\eta}Q^{k})_{sq}]} \qquad 4$$

$$\mathbf{\upsilon = c[\eta N - \Sigma\, (\eta Qk)sq]}$$

k=o 5

W = c[ηN – Σ (ηQkR)sq]

k=o 6

Equation (3) gives the variances of payments and bad debt. The components of $\mathbf{A}_{rt}$ give the standard deviations of these same values.

Equation (4) gives the variances of the components of **CN.**

Equation (5) gives the variances of the components of **CNε** and

Equation (6) gives the variances of the components of **CNR**

Estimation Techniques

The estimation technique adopted for this research is the Markov chain. Ordinary Least Square (OLS) a mathematical tool was used to determine the transition probability or loss expectancy rate for determining the amount of debt to be written off. The current practice among Nigeria banks uses the prudential guideline. The superiority of the Markov chain is determined largely by the ***memoriless*** property of Markov chain.

Data Presentation Analyses and Discussion

The data of this research are presented and analyzed in this section on the basis of the research objectives. The first section after this brief introduction, examines the current method adopted by the banking institutions in Nigeria in estimating bad debts value, that is, amount to be written off of the outstanding loans and advances of the bank. The second section evaluates the impact of the proposed stochastic method that is the Markov Chain, in estimating bad debts in the Nigerian banking sector. The third section ascertains the superiority of the proposed model over the traditional method of estimating bad debts in the Nigerian banking sector. The final section discusses the implications of these findings in line with relevant literature.

Presentation of Data

Table 4.1. *Annual Loans and Advances for Selected Economic Sectors and Aggregate.*

Sector /Year	2015 (₦‘000,000)	2014 (₦‘000,000)	2013 (₦‘000,000)	2012 (₦‘000,000)	2011 (₦‘000,000)
Agriculture	21,977	18,226	15,348	16,077	15,270
Oil and Gas	128,393	93,537	63,380	19,384	19,025
Personal	29,680	20,906	17,802	12,279	8,683
Manufacturing	44,536	38,490	23,830	9,395	15,565
Column Total	224,586	171,159	120,360	57,135	58,543
Aggregate Annual Loans	**348,984**	**302,372**	**210,118**	**136,982**	**144,358**
% of Sectors Aggregate	**64.35**	**56.61**	**57.28**	**34.85**	**40.55**

Source: *Union Bank plc Annual reports/Accounts and Author’s Field Work (2016)*

A cursory review of the aggregate loans and advances disbursed by the bank over the periods under consideration reveals there is a general increase except 2012 in the annual disbursement to customers.

This translates to a 5% decrease over 2011 for 2012 and 54% increase over 2012 for 2013 advances. Others are 44% increase over 2013 for 2014 financial year and 12% increase for the year 2015. The loans and advances of selected sectors of agriculture, Oil and gas, personal and manufacturing represent 40.55%, 34.85%, 57.28%, 56.61% and 64.35% respectively of the aggregate loans and advances.

Table 4.2. *Maturity of Loans and Advances*

Maturity/Year	2015	2014	2013	2012	2011
Less than 1 Month	66,307	57,451	39,922	26,027	27,428
1 – 3 Months	76,776	66,522	46,226	30,136	31,759
3 – 6 Months	31,409	27,213	18,911	12,328	12,992
6 – 12 Months	48,858	42,332	29,417	19,177	20,210
More than 12 Months	125,634	108,854	75,642	49,314	51,969
Aggregate	**348,984**	**302,372**	**210,118**	**136,982**	**144,358**

Source: *Union Bank plc Annual Reports/Accounts and Author’s Field Work (2016)*

A critical examination of the bank’s loans and advances maturity as shown in Table 4.2, reveals that union bank is most concern when the age of the facility is between 1 to 3 months, followed by loans and advances that falls due within 1 month. It equally shows that advances and loans which status is between 6 to 12 months come next in their concern list while loans and advances that matures within 3 to 6 months are of least on the bank watch list.

Table 4.3. *Perception of customers credit Status (Aggregate)*

Year	Performing	Substandard	Doubtful	Aggregate
2015	143,083	31,409	48,858	**223,350**
2014	123,973	27,213	42,332	**193,518**
2013	86,148	18,911	29,417	**134,478**
2012	56,163	12,328	19,177	**37,118**
2011	59,187	12,992	20,210	**92,389**

Source: *Union Bank plc Annual Reports/Accounts and Author's Field Work (2016)*

Table 4.3, highlights the bank's perception of customers credit status. As Table 4.3 reveals, that 64% of the loans and advances are all performing while 22% of the customers' accounts are doubtful and 14% of customers' accounts are included in the bank watch list classified as substandard.

Table 4.4. *Perception of customers credit Status on Sectoral basis*

Year	Sector	Sector Total (₦,000,000)	Sector Performing (₦,000,000)	Sector Substandard (₦,000,000)	Sector Doubtful (₦,000,000)
2015	Agriculture	21,977	9,010	1,978	3,078
	Oil and Gas	128,393	52,641	11,555	17,975
	Personal	29,680	12,169	2,671	4,155
	Manufacturing	44,536	18,260	4,008	6,235
2014	Agriculture	18,226	7,473	1,640	2,552
	Oil and Gas	93,537	38,350	8,418	13,095
	Personal	20,906	8,571	1,882	2,927
	Manufacturing	38,490	15,781	3,464	5,389
2013	Agriculture	15,348	6,293	1,381	2,149
	Oil and Gas	63,380	25,986	5,704	8,873
	Personal	17,802	7,300	1,602	2,492
	Manufacturing	23,830	9,770	2,142	3,336
2012	Agriculture	16,077	6,592	1,447	2,251
	Oil and Gas	19,384	7,947	1,745	2,714
	Personal	12,279	5,034	1,105	1,719
	Manufacturing	9,395	3,852	846	1,315
2011	Agriculture	15,270	6,261	1,374	2,138
	Oil and Gas	19,025	7,800	1,712	2,664
	Personal	8,683	3,560	781	1,216
	Manufacturing	15,565	6,382	1,401	2,179

Source: *Author's Field Work (2016).*

An examination of Table 4.4 reveals that 41% of bank customers' credits are performing. Oil and gas was the most performing sector with the Agricultural sector as the least performing. The table also revealed that 14% customers have doubtful accounts with the bank. The category was top by Oil and gas, followed by manufacturing, personal and agriculture. Finally on the basis of customers' sectoral distribution, 9% of the customers' accounts are perceived to be substandard.

Discussion of Findings

Here the findings of this research are presented according to the objectives stated for this study.

Our findings revealed that the bank entirely complies with the provisions of the Central Bank of Nigeria (CBN) as contained in the prudential guidelines (2010), to estimate the expected amount to be written off from loans and advances. The provision specified the basis of 10% for substandard accounts and 50% for doubtful accounts. In our opinion this is a rule of the thumb approach of determining bad debt value to be written off. The findings as shown in Table 4.5 seem to contradict the higher premium placed on doubtful accounts as against the substandard accounts in practice.

Table 4.5. *Traditional method of Estimating Aggregate Amount Lost*

Year	Aggregate Amount Lost

2015	**S** 32,409 **D** 48,858	10% 50%	3,141 24,429	27,570
2014	**S** 27,213 **D** 42,332	10% 50%	2,721 21,166	23,887
2013	**S** 18,911 **D** 29,417	10% 50%	1,891.1 14,708.5	16,600
2012	**S** 12,328 **D** 19,177	10% 50%	1,232.8 9,588.5	10,821
2011	**S** 12,992 **D** 20,210	10% 50%	1,299.2 10,105	11,404

S = SUBSTANDARD D = DOUBTFUL

Source: *Author's Field Work (2016).*

Table 4.6. *Traditional Estimation of Amount Lost on Sectoral Basis*

Year	Sector	Amount Lost (N000,000) on Sectoral Basis			
2015	**Agriculture**	**S** 1,978 **D** 3,078	10% 50%	198 1,539	1,737
	Oil and Gas	**S** 11,555 **D** 17,975	10% 50%	1,155.5 8,987.5	10,143
	Personal	**S** 2,671 **D** 4,155	10% 50%	267 2,078	2,345
	Manufacturing	**S** 4,008 **D** 6,235	10% 50%	400.8 3,117.5	3,518
2014	**Agriculture**	1,640 2,552	10% 50%	164 1,276	1,440
	Oil and Gas	8,418 13,095	10% 50%	841.8 6,547.5	7,389
	Personal	1,882 2,927	10% 50%	188.2 1,463.5	1,652
	Manufacturing	3,464 5,389	10% 50%	346.9 2,694.5	3,040
2013	**Agriculture**	1,381 2,149	10% 50% 10% 50%	138.1 1,074.5	
	Oil and Gas	5,704 8,873	10% 50%	570.4 4,436.5 5,007	1,213
	Personal	1,602 2,492	10% 214 50% 1,668 1,882	160 1,246 1,406	
	Manufacturing	2,142 3,336			
2012	**Agriculture**	1,447 2,251	10% 50%	144.7 2,225.5	1,270
	Oil and Gas	1,745 2,714	10% 50%	174.5 1,357	1,532
	Personal	1,105 1,719	10% 50%	110.5 859.5	970
	Manufacturing	846	10%	84.6	

		1,315	50%	657.5	742
2011	**Agriculture**	1,374 2,138	10% 50%	134 1,069	1,206
	Oil and Gas	1,712 2,664	10% 50%	171 1,332	1,503
	Personal	781 1,216	10% 50%	78 608	686
	Manufacturing	1,401 2,179	10% 50%	140.1 1,089.5	1,230

S = SUBSTANDARD D = DOUBTFUL

Source: *Author's Field Work (2016).*

The findings of this study on sectoral basis reveals that on year by year basis oil and gas reported the highest amount of indebtedness followed by manufacturing and agriculture and the sector with the least indebtedness is personal loans and advances. This suggests that the active sector of the economy have the tendency f loan default. This finding is contrary to expectation were the inactive sector (agriculture and personal) exhibit high level of loan default.

The second objective of this research is propose an estimation technique that would demonstrate the superiority over the traditional method of bad debt estimation.

Table 4.7. *StochasticModel forEstimating Aggregate Amount Paid and Lost*

Year	Amount Paid (₦,000,000)	Amount Lost (₦ 000,000)
2015	18,008	4,502
2014	15,602	3,901
2013	10,842	2,711
2012	7,068	1,767
2011	7,449	1,862

Source: *Author's Field Work (2016).*

Table 4.7 shows the aggregate amount paid and lost for the various years. A close look at Table 4.7 indicates that there was a 5% decrease on 2012 in the amount paid and lost. Also the analysis shows an increase of 53%, 44%, and 15% respectively over the preceding years. In 2012 there was a 5% decrease in the amount paid and lost, this suggest a more effective bad collection drive over the previous year. In this same vein, the results show a decreasing increase in the amount paid and lost in the preceding years. The implication of this finding is that this method is able to be conservative in estimating the amount expected to be paid and lost in every transaction.

Table 4.8. *StochasticModel forEstimating Paid and Lost on sectoral basis*

Year	Sector	Amount Paid (₦,000,000)	Amount Lost (₦,000,000)
2015	Agriculture Oil and Gas Personal Manufacturing	1,134 6,625 1,531 2,298	284 1,656 383 575
2014	Agriculture Oil and Gas Personal Manufacturing	941 4,826 1,079 1,986	235 1,207 270 497
2013	Agriculture Oil and Gas Personal Manufacturing	792 3,270 919 1,229	198 818 230 307
	Agriculture	830	207

2012	Oil and Gas Personal Manufacturing	1,000 634 485	250 158 121
2011	Agriculture Oil and Gas Personal Manufacturing	803 982 448 803	201 245 112 201

Source: *Author's Field Work (2016).*

The findings of this study on sectoral basis reveals that on year by year basis oil and gas reported the highest amount paid and lost followed by manufacturing and agriculture and the sector with the least amount paid and lost is personal loans and advances. This seems to indicate that oil and gas and manufacturing as the active sector of the economy have the tendency of loan default. This finding is contrary to expectation were agriculture and personal regarded as the inactive sector exhibit low level of loan default (Osaze, 2010).The final objective of this study is to demonstrate the superiority of stochastic method of debt estimation over the traditional method (CBN Prudential guideline 2010). Here we compared the amount lost using the traditional and stochastic methods.

Table 4.9. *Comparison of Aggregate Amounts Lost*

Year	Amount Lost (₦ 000,000) Traditional Method	Amount Lost (₦ 000,000) Proposed Model
2015	27,560	4,502
2014	23,887	3,901
2013	16,600	2,711
2012	10,821	1,767
2011	11,404	1,862

Source: *Author's Field Work (2016).*

In 2011 there was a 9542 decrease in the amount lost representing 319% in the amount expected to be saved when the stochastic method is adopted as shown in Table 4.11. The findings in 2012 also report a 9054 decrease in the amount estimated to be lost when the proposed method is employed. This outcome indicates a 512% savings in the amount to be written off the books of the bank. In 2013, 2014 and 2015 respectively, there was 13889, 19986 and 23058 respective decrease in the amount expected to be lost. This translates to 512% increase in the amount to be appropriated in the final accounts in each year. These findings have implication on the financial position of the bank, investors' wealth and liquidity of the economy. Finally, in order to have detail understanding of the effect of the stochastic method on bad debt estimation, we also undertook a sectoral analysis of the outstanding balances of customer's loans and advances.

Table 4.10. *Comparison of Amount Lost on Sectoral Basis*

Year	Sector	Traditional Method	Proposed Method
2015	Agriculture Oil and Gas Personal Manufacturing	1,737 10,143 2,345 3,518	284 1,656 383 575
2014	Agriculture Oil and Gas Personal Manufacturing	1,440 1,497 1,652 3,041	235 1,207 270 497
2013	Agriculture Oil and Gas Personal Manufacturing	1,213 5,007 1,406 1,882	198 818 230 307
2012	Agriculture Oil and Gas	1,270 1,532	207 250

	Personal Manufacturing	970 742	158 121
2011	Agriculture Oil and Gas Personal Manufacturing	1,206 1,503 686 1,230	201 245 112 201

Source: *Author's Field Work (2016).*

As shown in Table 4.12, in 2011, there was a difference of 1005 in the agriculture sector in the amount expected to be lost which represents 500% savings when the stochastic method is employed. In similar vein personal and manufacturing sector reports a 512% savings each while oil and gas report 513% when the proposed method is adopted. In 2012, findings shows that both oil and gas sector and personal exhibits a 512% increase in the amount saved when stochastic method is used and a 513% for agriculture and manufacturing respectively. A look at 2013 reveals that agriculture and manufacturing jointly reported the highest savings of 513% when stochastic method is adopted while it shows 512% and 511% for oil and gas and personal respectively. Also, with the adoption of stochastic method oil and gas reported a 24% savings in the estimated amount expected to be lost. The report reveals that It was 512% each for personal and manufacturing and finally 513% savings for agriculture in 2014. Finally, the findings in 2015 shows that apart from oil and gas with 513% difference following the adoption of stochastic method, the three other sectors of agriculture, personal and manufacturing reports a 512% difference.

Managerial Implications of Findings

The implications of the findings of this research are presented as follows. Financial managers are saddle with the responsibility of effectively and efficiently manage debt created in the course of business transactions.

This can only be done when the process of credit creation is strictly monitored and a realistic method that takes into consideration customers behavioural practices is adopted. One striking revelation of this study was banks high preference of the oil and gas sector to be granted credit facilities. This could suggest that banks perceive this sector most secured to be granted loans. This position is an affirmation of fact that the petroleum industry is seen as the main driver of Nigeria economy. The implication is that a downturn in the sector could cause crisis in the entire economy. According to Toby (2011), investment in the oil and gas sector in Nigeria is essentially investment in speculative trading. We are of the opinion that oil and gas sector requires loans to fund speculative trading rather encourages long term investment that drive the economy. This seems to be in tandem with the short term funding responsibility of banks. Despite the high preference for the oil and gas sector, the research reveals that it has the largest proportion of nonperforming loans and advances. This finding has serious implication on the banks financial position. In a similar vein, agriculture sector was reported to be most risky sector to grant loans. This is evident in the small proportion of loans granted. This position is unexpected despite the Federal government deliberate policy that encourages investment in agriculture. It is our opinion that continuation of this practice could hinder government effects in the promotion of agricultural sector. Another matter that is of concern to managers is in the amount to be written off when the provisions of CBN prudential guidelines. The results of the various computation shows that there are large amounts expected to be written off. This implies that the total amount to be appropriated by investors will decrease. When the equity return ratio is low, investors' confidence will be low and consequently it will take longer time for investors to recoup their investments. This could lead to de investment in the portfolio. Finally, when the proposed method is adopted there was a more reasonable amount to be written off the closing balance sheet figures. The implications are twofold. One, there will be higher level of liquidity in the economy and secondly, investors' confidence will soar high as they are entitled to more wealth arising from their investment in the portfolio.

Conclusion

This research examines stochastic approach to debt management in Nigeria banking sector. A close review of debt management in Nigeria reveals that CBN regulates the activities of all banks. To this extent, all the banks in Nigeria manage their debt in compliance with CBN's 2010 prudential guideline. This prudential guideline method of estimating the amount to be written is in our opinion non-scientific, as it does not make provision for behavioural differences of customers. This study however advocates a stochastic method be employed for the purpose of estimating the amount to be finally written off the accounts of banks. This is premised on the belief that stochastic model is scientific and takes into consideration customers behavioural characteristics.

It is our contention that the underlying benefits from such adoption are underscored by a system that emphasizes conservatism in estimating the income to be written off, and a financial statement that approximate the true position of affairs for the year. It is also our belief that this method when adopted by banks will in addition encourage a more aggressive debt recovery drive and more stringent measures in loans advancement.

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Citation: *Frank Alaba Ogedengbe (Phd)" Analysis of the Stochastic Approach to Debt Management in the Banking Sector in Nigeria", Journal of Banking and Finance Management, vol.2, no.1, pp. 43-59,2019.*