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# Relevance of Accounting Theory in Forecasting Techniques and Default Prediction in an Organization in Nigeria

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**Abstract**
Much have been done on forecasting and default or bankruptcy prediction, but not many of the earlier works have dwelt considerably on connecting accounting theory with the topic. This paper examines the relevance of accounting theory as a tool in forecasting techniques and default prediction in an organization in Nigeria, using organisations in industrial goods industry (sector) as a study area. Ex-post facto design is used this study because no attempt is made to control or manipulate relevant independent variables. Published financial statements of twelve (12) companies in the consumer goods sector with financial statements and reports covering the period of 2012 to 2017 are used. Findings revealed that liquidity ratios, leverage ratios and market ratios significantly predict and forecast firm default probability, while profitability do not significantly predict default likelihood. It is recommended that every stakeholders and entity issuing financial statements to ensure adequate disclosure of all relevant and material facts in the report to aid the analysts and other users make informed judgement from the content of the report.
**Key words:** Accounting Ratios, Accounting Theory, Bankruptcy Probability, Corporate Default, Default Predictions, Forecast Techniques.

## 1.0 Introduction

For over 100 years, financial statement analysis has been used to assess a company's likelihood of financial distress — the probability that it will not be able to repay its debts. Financial statement analysis was used by credit suppliers to assess the credit worthiness of its borrowers. In many cases, there was little alternative, reliable information, other than the general reputation of the borrower.

Predicting corporate default has been of a great concern to all stakeholders. This received more attention in the wake of the event of global financial crisis in 2007, which started in USA with subprime lending crises that lasted until mid-2010 (Soludo, 2009). Consequently, the global financial scene had witness many voices calling for a revolution of existing default warning systems in order to identify or prevent recurring default problems. Many studies evident that firms follow leverage targets (Graham and Harvey, 2001; Fama and French, 2002; Flannery and Rangan, 2006) as cited in 'Corporate Default Prediction with Industry Effects: Evidence from Emerging Markets' (International Journal of Economics and Financial Issues Volume 6: Special Issue, 2016). It can be said that any wrong decision about capital structure may lead the firm to financial distress and eventually to bankruptcy (Eriotis, 2007). Although, the impact of external factors is very important element that should be considered, this is not sufficient to hold such factors more relevant than the concepts underpinning the accounting practice.

The problem of predicting default can be viewed as a problem in assessing the probability of financial distress conditional upon the value of a ratio (or set of ratios). In arriving at estimates of the conditional probability of financial distress, the possible events are viewed as being dichotomous - either the firm will experience financial distress or it will not. Prior to looking at the financial ratios of the firm, certain prior probabilities are formed.

Early research works have not substantially connected accounting theory to the topic of organisation default. This paper therefore studies the extent to which accounting ratios signal, forecast or predict the possibility of corporate default or bankruptcy, using data obtained from the Industrial Goods Industry in Nigeria.

## 2.0 Literature Review

### 2.1 Conceptual Framework

Researchers since the 1930s have responded to the need for forecasts by conducting experiments testing multiple reasonable methods and the findings from those experiments have led to great improvements in knowledge about forecasting (Armstrong & Kesten, 2017).
For qualitative forecasts- such as whether a, b, or c will happen, or which of x or y would be better—accuracy is typically measured as some variation of percent correct. For quantitative forecasts, accuracy is assessed by differences between ex ante forecasts and data on what actually transpired. Therefore, the benchmark error measure for evaluating forecasting methods is the easily understood and decision-relevant Relative Absolute Error, abbreviated as "RAE" (Armstrong & Collopy 1992).

Many studies, research works and textbooks focus attention on sophisticated approaches for simplistic and economic based models that have very little relation to accounting practice in forecasting the likelihood of default in an organisation. Prior studies support the importance of industry effects on probability of default. (Opler & Titman, 1994) find that the adverse consequences of leverage on bankruptcy are more pronounced in concentrated industries and that single information can affect the industries differently across the whole market. Therefore, industries tend to have different issues and challenges, which could differently influence the default probability of firms. For that reason, industry and environment play significant role in explaining the organisational volatility (Nishat, 2001). As a result, most of the past studies conclude by depending heavily on the industry effect in forecasting and predicting default.

Accounting data as an easily accessible and a primary source of information provides the context, on which researchers could develop their prediction and base their forecasting activities. (Michael, 2015). The literature identifies the industry effects on probability of default but the argument seems to stand under-explored in the context of emerging markets. A number of studies tend to ignore the significance of industry in their model specification. In addition, researchers face problem in establishing the industry- specific variables due to data limitations. Therefore, most of the past studies removed the industry effect by including an industries dummy (Chava & Jarrow, 2004). However, prior studies support the importance of industry effects on probability of default. Opler and Titman (1994) find that the adverse consequences of leverage on bankruptcy are more pronounced in concentrated industries. In related research, Lang and Stultz (1992) reveal competitive intra-industry effects of bankruptcy announcements. According to Acharya and Srinivasan (2003), industry conditions at the time of default affect the recovery rate. The argument between firm-specific and industry effect is indecisive across emerging markets. However, there exist enormous institutional differences. As well, the effect of sectoral behaviour on probability of default determinants may differ across different markets. Despite that, the unique behaviour of each industry varies between countries due to different financial settings. It is affirmed that, the lack of developed bond markets is often one of the reasons for the intensity of the financial crisis across developing countries. As the financial system in most emerging and developing economies is centred on banks, an important aspect of the development of bond markets is the impact on the banking system. Since the Asian financial crisis of 1997-98, attention has increasingly focused on the relative roles of the banking sector and of the capital market in developing economies. In many instances, the domestic bond market, where it exists, is generally under-developed, in both breadth and depth, compared to the banking system and the equity market. It has been argued that, over-reliance on bank lending for debt financing exposes an economy to the risk of a failure in the banking system.

According to Noravesh, Dilami and Bazaz (2007), Iranian industries are heavily dependent on bank financing, which has been shown to affect the investment decisions of firms. Consequently, during uncertain macro environment, banks are resistant to advance long-term loans to the private industries, and often retreat to short-term lending. Based on significance of industries in the performance of firms, it reveals the importance to investigate the industry effects on probability of default of firms in emerging economies.

### 2.1.1 Accounting Theory

A 'theory' according to Oxford Advanced Learners' Dictionary, Oxford University Press, (2010) is a formal set of ideas that is intended to explain why something happens or exists; the principles on which a particular subject is based or an opinion or idea that somebody believes is true but that is not proved. Theory is used sometimes to say that a particular statement is supposed to be true but may in fact be wrong.

According to Kerlinger, (1973) Theory can be defined as a set interrelated constructs, (concepts), definition or proposition that present a systematic view of phenomena by specifying relations among variables with the purpose of explaining or predicting the phenomena.

Henderiksen (1970) defined theory as 'a set of hypothetical, conceptual and pragmatic principles forming the general framework of reference for a field of liquidity'.

### 2.1.2 Forecasting Techniques and Methods

Accuracy is the most important criterion for most parties concerned with forecasts (Fildes & Goodwin 2007). The predictive validity of a forecasting method is assessed by comparing the accuracy of forecasts from the method with forecasts from the currently used method, or from other evidence-based methods. For qualitative forecasts—such as whether a, b, or c will happen, or which of x or y would be better—accuracy is typically measured as some variation of percent correct. For quantitative forecasts, accuracy is assessed by differences between ex ante forecasts and data on what actually transpired. The benchmark error measure for evaluating forecasting methods is the easily understood and decision-relevant Relative Absolute Error, abbreviated as "RAE" (Collopy & Armstrong, 1992).

There are many forecasting techniques, but we have basically two approaches to forecasting; these are, qualitative and quantitative.

In qualitative approach, forecasts are based on judgment and opinion, for instance, executive opinions, Delphi technique, sales force polling, consumer surveys, techniques for eliciting experts' opinions - PERT derived. In quantitative approach, forecasts are based on (1) historical data, these include; naive methods, moving averages, exponential smoothing, trend analysis, decomposition of time series and box-Jenkins. (2) Associative (causal) forecasts, here, we have simple regression, multiple regression, econometric modelling. (3) Consumer behaviour oriented forecast such as the Markov approach and (4) Indirect methods which comprises of market surveys, input-output analysis and economic indicators. These are discussed in detail below:

#### 2.1.2.1 Qualitative/Judgmental Methods

This is the use of expertise based on experience in similar situations, using for example relative frequencies. Experience can also lead to the development of simple "rules of thumb," or heuristics that provide quick forecasts that are usually sufficiently accurate for making good decisions, such as choosing between options. The superiority of simple heuristics for many recurrent practical problems has been shown by extensive research conducted by Gigerenzer and the ABC Group (1999) of the Max Planck Institute for Human Development in Berlin cited in Armstrong and Kesten, (2017). Goodwin, 2017 also describes situations where expertise, translated into rules-of-thumb helps to make accurate forecasts. Generally, it has been established that unaided expert judgment should be avoided for complex nonrecurring situations for which simple heuristics have not been shown to be valid. For such situations, structured judgmental methods are needed; nine of such evidence-based structured methods are identified. The methods include Intentional surveys, Expectation surveys, Expert surveys, simulated interaction, structured analogies, Experimentation and Expert systems.

#### 2.1.2.2 Quantitative Methods

Quantitative methods use some typically numerical data related to what is being forecast. These methods make use of judgmental methods, such as decomposition. This study focuses on the regression analysis forecasting methods. Regression analysis is useful for estimating the strength of relationships between the variables and one or more known causal, or predictor, variables. Regression analysis is an important tool for quantifying relationships. One of the benefits of regression analysis is that it is conservative, in that it reduces the size of coefficient estimates to adjust for random measurement error in the variables. Much literature over the years has however concluded that the validity of regression estimated model parameters has been poor. (Ioannidis, Stanley & Doucouliagos cited by Armstrong & Green (2017).

### 2.1.3 Corporate Default Prediction

The ability of account users to perform accurate assessment of a firm's likelihood of default using publicly available sources of default risk information is critical for efficient resource allocation. For example, (Campbell, Hilscher and Szilagyi 2008) document that are more likely to experience financial distress have higher volatility and greater non-diversifiable risk.

### 2.1.4 Corporate Default Drivers

The choice of default drivers extensively in previous literature remains ambiguous. Campbell, Hilscher and Szilagyi (2008) make use of firm-level market information, Duffie, Saita and Wang (2007) recommends macroeconomic indicators using macroeconomic variables, Chava and Jarrow, (2004) suggests industry effect while Altam, (2000) recommends and adopts accounting ratios. Other non-numerically measurable drivers for instance, quality of a firm's assets, management creativity, the decisions of the regulator unsystematic or random events and courts of law, are suggested. This study corroborates the Altam stance as it looks into the place of accounting theory in all these.

### 2.1.5 Modelling Default or Bankruptcy Probability

Bankruptcy prediction has received increasing attention from the finance and accounting literature since the late sixties. Seminal research of Beaver (1967) started to analyse the antecedents of bankruptcy by leading a discriminant analysis on a single ratio (cash-flow/total debt) while Altman (1968) developed a multidimensional approach that combined five accounting ratios to calculate the well-known "Z-score" in order to predict corporate bankruptcy. Over years, numerous modelling techniques have been designed to provide a more complete understanding of the bankruptcy phenomenon and improve the accuracy of the models. In that sense, Du Jardin (2009) reveals that more than 50 methods have been used to build bankruptcy prediction models (discriminant analysis, logistic regression, probit regression, rules induction, spline regression, neural networks, gambler's ruin model, hazard model, and so on).

One of the most frequently employed statistical techniques in bankruptcy forecasts is the logit model (first used in Ohlson, 1980). This model offers several advantages that make it superior to alternative procedure. For instance, logit models do not require the potential bankruptcy predictors to be normally distributed and allow combining several bankruptcy indicators into a multivariate probability score which indicates the likelihood of corporate bankruptcy (Balcaen & Ooghe, 2006; Karlson, 2015). Given the reliability of logit models to assess corporate bankruptcy (Acosta-González & Fernández-Rodríguez, 2014; Gupta, Gregoriou & Healy, 2015), this statistical technique will be used in this study.

Beyond the regression technique, another point must be stressed to build accurate bankruptcy prediction model: variable selection. Usually, a two-step procedure is chosen to select the most accurate variables. Reviewing 190 papers on bankruptcy prediction models, Du Jardin (2009) showed that, during the first step, 40 per cent of studies only used variables that have been found to be good predictors in prior research. In other words, the variables are included in the model because they were significant in past empirical works. However, this procedure is quite reductionist as bankruptcy predictors can be reliable in one context but not in another owing to their contingent nature (Balcaen & Ooghe, 2006; Du Jardin, 2015). To mitigate this concern, the first step of this research proposes to adopt a mix-method that includes variables whose predictive power has been demonstrated in prior studies as well as ad hoc variables with the aim to improve the accuracy of the model.

In the second step, an automatic procedure is commonly employed to build the final set of bankruptcy predictors. Dash and Liu (1997) suggested distinguishing between complete methods and heuristic methods. While the former enables to find an optimal solution provided the evaluation criteria is monotonic, the latter relaxes the monotonic assumption on the selection criteria. As a result, heuristic procedures allow researchers to explore all possible combinations for the selection criteria to finally restrict attention to a smaller number of potential bankruptcy predictors (Acosta-González & Fernández-Rodríguez, 2014). Some of the most popular methods are the forward or backward stepwise procedures, which sequentially include or exclude variables based on various criteria such as t-ratio statistics or the probability of F (Miller, 2002; Lussier & Corman, 2015). Despite their relevancy, few studies engage in such procedures. According to Du Jardin (2009), only 26 per cent of prior works on bankruptcy prediction adopt a stepwise selection procedure, which hampers the robustness of their results.

This research uses Altman’s multidimensional approach to calculate the well-known “Z-score” in order to predict corporate bankruptcy (Altman, 1968).

#### 2.1.6 Accounting Ratios and Bankruptcy Probability

Accounting ratios were classified into four broad categories. Leverage ratios measuring the capability of a firm in paying its debt obligations. Liquidity ratios indicating a firm’s ability to pay its debt obligations using available cash at the firm’s disposal. Beaver (1966) argues that the firms with lower liquid assets are more prone to bankruptcy and vice versa, that is firms with higher liquidity show likely immunity against default. Four ratios are considered in measuring liquidity of a company in this study. Profitability ratios measure the effectiveness of the firm's use of resources. Profitability ratios measure the firms’ efficient and effective utilization of their assets and how they control their expenditure to produce adequate earnings for the shareholders. Here, what constitutes adequate earnings or rate of returns depends sometimes on the firm’s industrial average and market ratios measure investor response to owning a company's stock, these ratios also measure the cost of issuing stock. They are concerned with the return on investment for shareholders, and with the relationship between return and the value of an investment in company's shares.

 

**2.1.7 Conceptual Framework of Relevance of Accounting Theory in Forecasting Technique and Default Prediction in an Organisation in Nigeria**

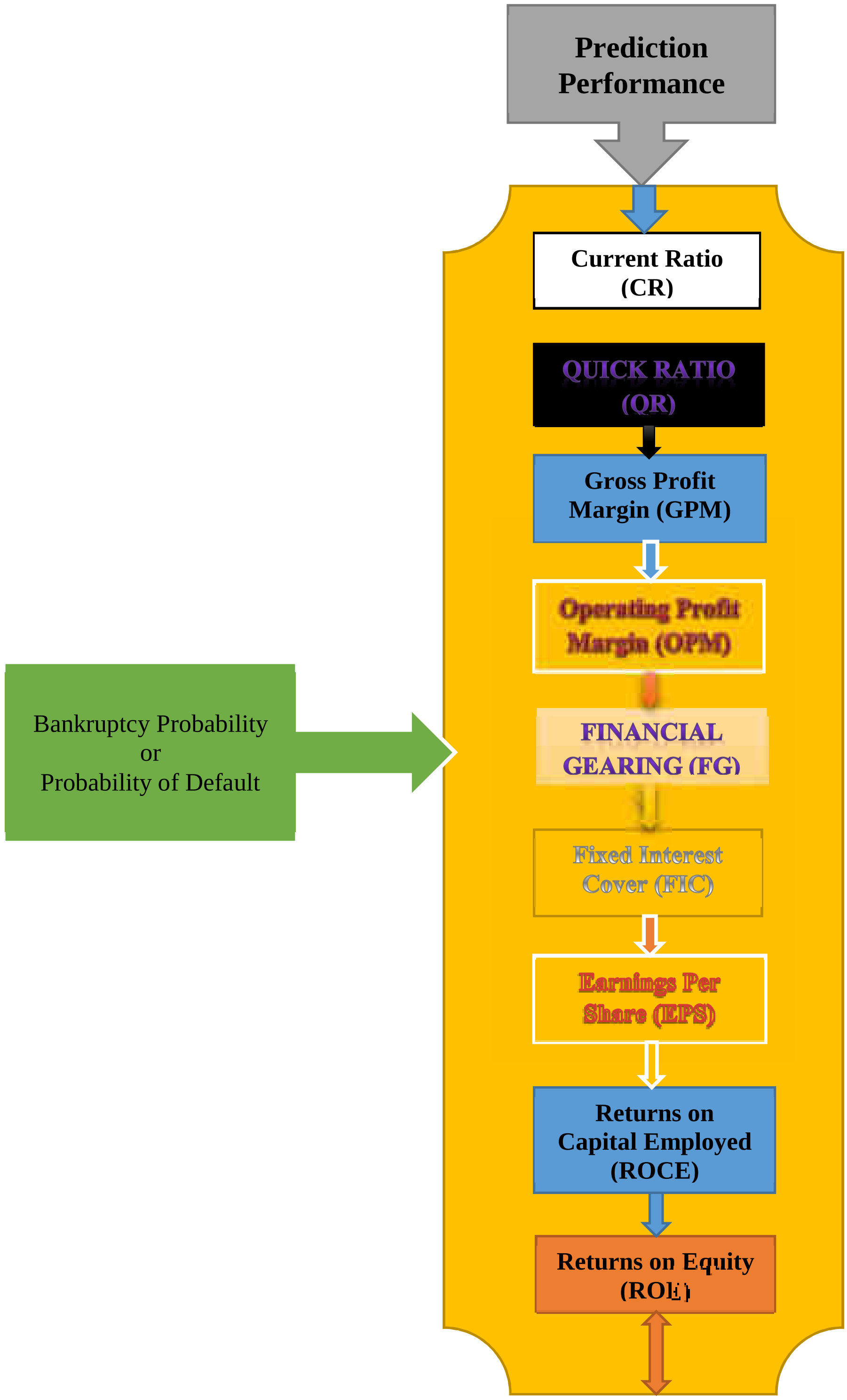


**Fig. 1: Source: Researchers' Conceptual Framework of Relevance of Accounting Theory in Forecasting Technique and Default Prediction in an Organisation in Nigeria Model**

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## 2.2 Theoretical Review

Accounting theory takes its root from decision theory, measurement theory and information theory.

### 2.2.1 Decision theory

Decision theory is an interdisciplinary approach to determine how decisions are made given unknown variables and an uncertain decision environment framework. Decision theory brings together psychology, statistics, philosophy and mathematics to analyse the decision-making process. The theory is the study of the reasoning underlying an agent's choices. Decision theory can be broken into three branches: normative decision theory, which gives advice on how to make the best decisions, given a set of uncertain beliefs and a set of values. Descriptive decision theory, which analyses how existing, possibly irrational agents actually make decisions; and prescriptive decision theory, which tries to guide or give procedures on how or what we should do in order to make best decisions in line with the normative theory. Decision theory is closely related to game theory and is studied within the context of understanding the activities and decisions underpinning activities. (investopedia.com)

### 2.2.2 Measurement theory

Measurement theory according to Glautier and Underdown (1978) cited in Agbiogwu (2015) holds the view that rational decision making depends on information or data, hence measurement to them implies assignment of rules specifying the property to be measured, the scale to be used and the dimension of the unit. The measurement theory is very important to the Accountant. Busch and Lahti (2012) see term measurement theory as referring to that part of a physical theory in which the empirical and operational content of the concepts of the theory is determined. Measurements are analysed both as operational procedures defining the observables of the theory and as physical processes which are themselves subject to the laws of physics.

### 2.2.3 Information Theory

Information in business generally is seen as the organizations resources and therefore is of paramount importance to the Accountant. It is a theory that deals statistically with information, with the measurement of its content in terms of its distinguishing essential characteristics or by the number of alternatives. Following the fact that information is a resource, information theory therefore emphasizes efficient utilization in relation to input and output.

## 3.0 Methodology

For this research work, ex-post facto design is used in this study. Data already exist as no attempt is made to control or manipulate relevant independent variables apparently, because these variables cannot be manipulated since the events have already taken place and therefore the research is being conducted after the fact. The study is conducted among companies in the Consumer Goods Sector quoted on the Nigerian Stock Exchange, between the periods 2012 – 2017. Data is obtained from the published financial statements of twelve (12) companies in the consumer goods sector with financial statements and reports covering the period of the study. Firm year observations without adequate data on studied variables are excluded, leaving a sample of 71 firm-year observation.

## 3.1 Model Specification

To test the research Hypotheses, the researchers run three regression models. The first equation models the relationship between selected accounting ratios in a given year and the bankruptcy probability for that given year. Equation 2 and 3 models accounting ratios implications in the prediction of future firm default, with Equation (2) predicting one year ahead bankruptcy or default probability, and Eqn. (3) forecasting the probability of default in two years' time.

$$BP_{it} = \beta_0 + \beta_1 CR_{it} + \beta_2 QR_{it} + \beta_3 GPM_{it} + \beta_4 OPM_{it} + \beta_5 GEAR_{it} + \beta_6 FIC_{it} + \beta_7 EPS_{it} + \beta_8 ROCE_{it} + \beta_9 ROE_{it} + \varepsilon_{it} \quad \ldots\ldots\ldots \quad 1$$

$$BP_{t+1} = \beta_0 + \beta_1 CR_{it} + \beta_2 QR_{it} + \beta_3 GPM_{it} + \beta_4 OPM_{it} + \beta_5 GEAR_{it} + \beta_6 FIC_{it} + \beta_7 EPS_{it} + \beta_8 ROCE_{it} + \beta_9 ROE_{it} + \varepsilon_{it} \quad \text{………} \quad 2$$

$$BP_{it+2} = \beta_0 + \beta_1 CR_{it} + \beta_2 QR_{it} + \beta_3 GPM_{it} + \beta_4 OPM_{it} + \beta_5 GEAR_{it} + \beta_6 FIC_{it} + \beta_7 EPS_{it} + \beta_8 ROCE_{it} + \beta_9 ROE_{it} + \varepsilon_{it} \quad \text{………} \quad 3$$

Where BP denotes bankruptcy probability or probability of default (measured using the Altman Bankruptcy Z-Score; expressed as a dummy variable. D=0 for Firms with default in payment, having a high probability of bankruptcy, i.e. Z<1, and D=1 for Firms with no default in payment, having a low probability of bankruptcy, i.e. Z>1); $BP_{it+1}$ denotes the probability of a firm going bankrupt or defaulting in one year time; $BP_{it+2}$ denotes the probability of a firm going bankrupt in two years' time.

## 4.0 Results

### 4.1 Descriptive Statistics

**Table 1:** Correlation Coefficient of Current Values of Variables Studied

| | CR | QR | GPM | OPM | GEAR | FIC | EPS | ROCE | ROE | B_PROB |
|---|---|---|---|---|---|---|---|---|---|---|
| CR | 1 | | | | | | | | | |
| | ----- | | | | | | | | | |
| QR | 0.950405 | 1 | | | | | | | | |
| | 0 | ----- | | | | | | | | |
| GPM | -0.365123 | -0.359373 | 1 | | | | | | | |
| | 0.0017 | 0.0021 | ----- | | | | | | | |
| OPM | -0.458773 | -0.390368 | 0.647326 | 1 | | | | | | |
| | 0.0001 | 0.0008 | 0 | ----- | | | | | | |
| GEAR | -0.10279 | -0.13215 | 0.104791 | 0.101394 | 1 | | | | | |
| | 0.3937 | 0.272 | 0.3845 | 0.4001 | ----- | | | | | |
| FIC | -0.144984 | -0.089726 | 0.200334 | 0.453466 | -0.101327 | 1 | | | | |
| | 0.2277 | 0.4568 | 0.0939 | 0.0001 | 0.4005 | ----- | | | | |
| EPS | -0.121697 | -0.075014 | 0.355059 | 0.56118 | 0.388148 | 0.266041 | 1 | | | |
| | 0.312 | 0.5341 | 0.0024 | 0 | 0.0008 | 0.0249 | ----- | | | |
| ROCE | -0.119033 | -0.111292 | 0.211653 | 0.151996 | 0.037927 | 0.172234 | 0.01755 | 1 | | |
| | 0.3228 | 0.3555 | 0.0764 | 0.2057 | 0.7535 | 0.1509 | 0.8845 | ----- | | |
| ROE | -0.139914 | -0.100096 | 0.470003 | 0.653506 | 0.341506 | 0.236277 | 0.839644 | 0.020885 | 1 | |
| | 0.2445 | 0.4062 | 0 | 0 | 0.0036 | 0.0473 | 0 | 0.8627 | ----- | |
| B_PROB | 0.132586 | 0.184041 | 0.252768 | -0.495748 | 0.153735 | 0.377243 | -0.118918 | -0.174237 | -0.100594 | 1 |
| | 0.2704 | 0.1244 | 0.0334 | 0 | 0.0205 | 0.0012 | 0.3233 | 0.1462 | 0.0404 | ----- |

**Source:** Researchers' Correlation Coefficient of current values of Variables studied E-views 9.5

CR and QR are variables representing Liquidity Ratios where CR denotes current ratio (measured as current assets over current liabilities) and QR denotes quick ratio (measured as current assets less inventory over current liabilities).

GPM and OPM are variables representing Profitability Ratios where GPM denotes Gross Profit Margin (measured as gross profit over sales), and OPM denotes Operating Profit Margin (measured as operating profits before interest and tax over sales).

GEAR and FIC are variables representing Leverage or Solvency Ratios where GEAR denotes Financial Gearing (measured as total debt over total capital), and FIC denotes Fixed Interest Cover (measured as Net Profit plus Fixed interest all over Fixed Interest).

EPS, ROCE and ROE are variables representing Market or Investors Ratios where EPS denotes Earnings Per Share (measured as profit distributable to shareholders over number of equity shares), ROCE denotes Returns on Capital Employed (measured as Net operating profit over total assets less current liabilities), and ROE denotes Returns on Equity (measured as Net Income over Shareholder's equity).

In order to fully predict the default probability of firms using the highlighted accounting ratios, the distributed lag model is introduced where the current values of the dependent variable are predicted based on both the current values and past values of the explanatory variables. Using two lags for each independent variable, the model will show how each one will predict the possibility of default from the current year up to two years' time. Thus, Equation (1) to (3) specified above can be presented in the standard distributed lag model below:

$$BP_{it} = \beta_0 + \beta_1 CR_{it} + \beta_2 CR_{it-1} + \beta_3 CR_{it-2} + \beta_4 QR_{it} + \beta_5 QR_{it-1} + \beta_6 QR_{it-2} + \beta_7 GPM_{it} + \beta_8 GPM_{it-1} + \beta_9 GPM_{it-2} + \beta_{10} OPM_{it} + \beta_{11} OPM_{it-1} + \beta_{12} OPM_{it-2} + \beta_{13} GEAR_{it} + \beta_{14} GEAR_{it-1} + \beta_{15} GEAR_{it-2} + \beta_{16} FIC_{it} + \beta_{17} FIC_{it-1} + \beta_{18} FIC_{it-2} + \beta_{19} EPS_{it} + \beta_{20} EPS_{it-1} + \beta_{21} EPS_{it-2} + \beta_{22} ROCE_{it} + \beta_{23} ROCE_{it-1} + \beta_{24} ROCE_{it-2} + \beta_{25} ROE_{it} + \beta_{26} ROE_{it-1} + \beta_{27} ROE_{it-2} + \varepsilon_{it} \ldots\ldots\ldots \quad 4$$

It is expected that any ratio that has predictive power over, or signals the default probability of firms should have a *p*-value less than 0.05 alpha levels, otherwise accept the null hypotheses.

From the above table 1, the Pearson moment correlation coefficient reveals positive yet not statistically significant association between liquidity ratios (i.e. current ratio and quick ratio) and default probability. Although a negative association is expected, the positive association explains the fact that in the current year, liquidity and default are not significantly related.

The association between profitability and default probability reveals that GPM is positively related with bankruptcy in a statistically significant manner, while OPM is negatively associated with default in a statistically significant fashion. This explains the fact that an increase in operating profitability is associated with decreasing default possibility. The relationship between default probability and solvency or leverage ratios reveal that both gearing and fixed interest cover ratios are positively associated with firm default rate at statistically significant rates. In other words, as solvency ratios increase, default probability increase too. This is in line with apriori expectations that firm insolvency is directly associated with its chances of bankruptcy.

Investment ratios association with default probability reveals that all investors or market ratios studied are negatively associated with default in the current year. While the association between ROE and default are statistically significant, the association between EPS and ROCE, and Default probability are not statistically significant. The negative association fits apriori expectations that firm value decreases with lower shareholder wealth, thus increasing the likelihood of firm default.

All the liquidity ratios are negatively related to all other ratios. The negative relationship between liquidity ratios and profitability ratios is statistically significant for both GPM and OPM. This could imply that the increase in profit without a corresponding increase in cash earnings. The negative relationship between liquidity ratios, solvency ratios and market ratios are not statistically significant for GEAR, FIC, EPS, ROCE, ROE.

The relationship between profitability ratios and leverage ratios and market ratios are positive. The positive relationship is statistically significant for FIC, EPS and ROE, and not statistically significant for GEAR and ROCE.

A positive relationship is also observed between leverage ratios and market ratios, with the positive relationship being statistically significant for EPS and ROE, and not statistically significant for ROCE.

 

## 4.2 Hypotheses Testing

**Table 2:** ARDL Regression Results of Accounting Ratios Prediction on Default Probability of Firms in the Industrial Goods Sector in Nigeria, 2012-2017.

| **PANEL A: Regression model of Liquidity Ratios predicting the probability of firm default** | | | | |
|---|---|---|---|---|
| | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.** |
| CR | -0.159876 | 0.063319 | -2.524940 | 0.0156 |
| CR(-1) | -0.051423 | 0.047910 | -1.073320 | 0.0289 |
| CR(-2) | -0.037210 | 0.059691 | 0.623384 | 0.0366 |
| QR | 0.672381 | 0.192275 | 3.496978 | 0.0612 |
| QR(-1) | -0.285138 | 0.154340 | -1.847465 | 0.0271 |
| QR(-2) | -0.109969 | 0.114282 | 0.962259 | 0.0342 |
| | | | | |
| **PANEL B: Regression model of Profitability Ratios predicting the probability of firm default** | | | | |
| | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.** |
| GPM | -0.981424 | 1.063211 | -0.923076 | 0.3615 |
| GPM(-1) | 1.180832 | 1.305910 | 0.904221 | 0.3713 |
| GPM(-2) | -0.172393 | 1.108039 | -0.155584 | 0.8771 |
| OPM | 1.958170 | 1.291436 | 1.516273 | 0.1373 |
| OPM(-1) | -1.692378 | 1.172111 | -1.443871 | 0.1566 |
| OPM(-2) | 1.308735 | 0.864415 | 1.514012 | 0.1379 |
| | | | | |
| **PANEL C: Regression model of Leverage Ratios predicting the probability of firm default** | | | | |
| | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.** |
| GEAR | 0.107066 | 0.218000 | 0.491126 | 0.6260 |
| GEAR(-1) | -0.105138 | 0.205943 | 0.510519 | 0.0125 |
| GEAR(-2) | -0.132131 | 0.211466 | -0.624834 | 0.0356 |
| FIC | -0.002960 | 0.005008 | -0.591166 | 0.5577 |
| FIC(-1) | 0.007436 | 0.005039 | 1.475825 | 0.1478 |
| FIC(-2) | -0.011188 | 0.005883 | -1.901890 | 0.0444 |
| | | | | |
| **PANEL D: Regression model of Investors' Ratios predicting the probability of firm default** | | | | |
| | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.** |
| EPS | 0.052574 | 0.060159 | 0.873916 | 0.3874 |
| EPS(-1) | -0.036637 | 0.046569 | -0.786729 | 0.4361 |
| EPS(-2) | -0.018907 | 0.057467 | -0.329007 | 0.0439 |
| ROCE | 2.307907 | 0.429622 | 5.371946 | 0.0000 |
| ROCE(-1) | -1.496759 | 0.479042 | -3.124485 | 0.0033 |
| ROCE(-2) | -0.035993 | 0.109394 | -0.329024 | 0.0439 |
| ROE | -0.042244 | 0.025293 | -1.670142 | 0.0127 |
| ROE(-1) | 0.003003 | 0.026480 | 0.113411 | 0.9103 |
| ROE(-2) | -0.060764 | 0.031091 | -0.217563 | 0.0289 |
| | | | | |
| **R-Squared = 0.92; Adjusted R-Squared = 0.86; F-Statistics = 16.10; *p*=0.000; DW=1.96** | | | | |

Source: Researchers' ARDL Regression Results

**Panel A**

The ARDL regression result presented in Panel A of table 2, signalling, predictive, and forecasting power of liquidity ratios on firm default or bankruptcy probability reveals the following. Current values of current ratio has a negative effect on default possibility, revealing over 15 per cent effect, which is significant at the 0.05 level

(i.e. $p$=0.01). CR (-1) effect on bankruptcy probability (BP) explains the predictive power of CR in one year ahead bankruptcy likelihood. The results show that CR negatively predicts one year ahead BP by 5 per cent, which is statistically significant (p=0.02). CR (-2) effect on bankruptcy probability (BP) explains the forecasting strength of CR on default probability in two year time. The results show that CR negatively forecast the chances of two year ahead BP by 3 per cent, which is statistically significant (p=0.03). This indicates that CR negatively signals the likelihood of default in the current year, and also negatively forecast future firm default.
Quick ratio (QR) results indicate that current year default likelihood is not influenced by QR. However, future bankruptcy probability is negatively predicted by QR, such that QR predicts about 29 per cent and 11 per cent of one year ahead and two years ahead BP respectively in a statistically significant manner (with $p$ = 0.02 and 0.03 for year 1 and year 2 predictions).
Thus, the null hypothesis is rejected, and the research hypothesis upheld that Liquidity ratios significantly predict firm default probability.

**Panel B**
The ARDL regression result presented in Panel B of table 2, signalling, predictive, and forecasting power of profitability ratios on firm default or bankruptcy probability reveals the following. Current values of GPM and OPM do not statistically signal the likelihood of default in the current year (with $p$=0.36 and 0.13 respectively). GPM (-1) and GPM (-2) measuring the predictive power of GPM on future bankruptcy likelihood does not appear to be statistically significant at the 0.05 level, implying that GPM does not predict firm bankruptcy probability (with p=0.37 and 0.87 respective for year 1 and year 2 prediction).

OPM results also indicate that future default probability is not predicted by current values of OPM. OPM (-1) and OPM (-2) measuring the predictive power of OPM on future bankruptcy likelihood does not appear to be statistically significant at the 0.05 level, implying that OPM does not predict firm default (with p=0.15 and 0.13 respective for year 1 and year 2 prediction). Hence, both GPM and OPM do not predict or forecast firm default. This is because an increase in profitability does not mean increase in cash earnings, thus, making the firms to unable to meet their financial obligations as at when due.

Thus, the null hypothesis is accepted that profitability ratios do not significantly predict firm default probability.

**Panel C**
The ARDL regression result presented in Panel C of table 2, signalling, predictive, and forecasting power of leverage ratios on firm default or bankruptcy probability reveals the following. Current values of financial gearing (GEAR) and fixed interest cover (FIC) do not have statistically significant bearing on the likelihood of firm default, with both ratios having p=0.62 and 0.55 respectively, greater than the 0.05 alpha level. GEAR(-1) effect on (BP) which explains the predictive power of GEAR on bankruptcy likelihood in one year time, reveals a negative prediction of 11 per cent, which is statistically significant (p=0.01). GEAR(-2) effect on bankruptcy probability (BP) which explains the forecasting strength of GEAR on default probability in two year time reveals that GEAR negatively forecasts BP by 13 per cent, which is statistically significant (p=0.03). This indicates that GEAR negatively signals the likelihood of future firm default.

FIC implications on future default likelihood show that FIC negatively and significantly predict about 1 per cent of bankruptcy probability of Industrial Goods firms in two years time, in a statistically significant manner (with $p$ = 0.04). This indicates that FIC negatively signals the likelihood of future firm default.

Thus, the null hypothesis is rejected, and the research hypothesis upheld that leverage ratios significantly predict firm default probability.

**Panel D**
The ARDL regression result presented in Panel D of table 2, signalling, predictive, and forecasting power of market ratios on firm default or bankruptcy probability reveals the following. Current values of ROCE and ROE

have statistically significant bearing on the likelihood of firm default, with both ratios having *p*=0.00 and 0.01 respectively, less than 0.05 alpha level. GEAR(-1) effect on (BP) which explains the predictive power of GEAR on bankruptcy likelihood in one year time, reveals a negative prediction of 11%, which is statistically significant (p=0.01). EPS(-2), ROCE(-2) and ROE(-2) effect on bankruptcy probability (BP) which explains the forecasting strength of market ratios on default probability in two year time reveals that these market ratios negatively forecasts BP by 2 per cent, 4 per cent and 6 per cent respectively, which is statistically significant (*p*=0.04, 0.04 and 0.02). This indicates that market ratios negatively signal the likelihood of future firm default.

Thus, the null hypothesis is rejected, and the research hypothesis upheld that market ratios significantly predict firm default probability.

**5.0 Summary and Conclusion**

Bankruptcy prediction, otherwise known as 'firm default' prediction is a critical issue that has been widely explored and elaborately argued in the finance and accounting literature. For decades, the ultimate goal of the most of the prediction models was (and it still is) to increase the prediction power of the models. Mostly, this leads to some complicated techniques. Varieties of factors ascertain the quality of an econometric study, including the model and the data. The robust approaches endeavour to initiate reliable and accurate models, by considering noteworthy determinants and well-founded techniques.

This study focused on the predictive and forecasting power of accounting theory (measured as ratios) on firm default prediction, using the Autoregressive distributed lag (ARDL) model to predict future default likelihood up to two years. The models suggest that bankruptcy can be predicted by a subset of nine variables: current ratio, quick ratio, gearing, fixed interest cover, gross profit margin, operating profit margin, earnings per share, returns on capital employed and returns on equity, computed from four accounting ratios; liquidity, profitability, leverage and market ratios whose predictive power has already been shown (e.g. Altman, 1968). The results reveals that liquidity ratios, leverage ratios and market ratios significantly predict and forecast firm default probability, while profitability do not significantly predict default likelihood.

In conclusion, it is incumbent upon every stakeholders and entity issuing financial statements to ensure adequate disclosure of all relevant and material facts in the report to aid the analysts and other users make informed judgement from the content of the report. It is through this, the financial statements could fulfil one of its role as a tool for forecast technique and default prediction. This should also include stiff penalties for non-compliance.

This study suffers from several limitations that must be acknowledged. First, the use of Altman Z-Score computation for the computation of bankruptcy probability. Even if using such a procedure has been found reliable, there is the chance of having an over-identification concern emanating from the five parameters of the model, meaning that false significant variables could be included in the final model (Lovell, 1983).

Therefore, it is suggested that future research should adopt a method that alleviates this problem such as computational search procedures or data mining and machine learning techniques.

Finally, this study examined bankruptcy prediction using a sample of firms in the industrial goods industry. It is hoped that, by developing a further understanding of bankruptcy prediction among firms in the same industry, this study will stimulate future research on this complex and important issue of finance and accounting studies across different industries within the Nigerian business environment.

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