Modeling Default Rates on Macroeconomic and Business Cycle Dynamics In The Nigerian Banking Industry: A Factor Analysis Approach

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ABSTRACT
The emergence of Basel II made this study on modeling default rates on macroeconomic and business factors using the Factor Analysis approach has made credit risk management crucial to growth and stability of financial institutions. The study stands on the theoretical foundation of Black, Scholes and Merton’s Option Pricing Theory and the Cash Flow Theory of Default. In carrying the Dynamic Factor Analysis, selected variables cued under factors such as business cycle, stock market, banking regulatory macroeconomic and price indicators independent (exploratory) while default rate as dependent. Data of this study were gotten from the secondary source and covered a period ranging from 2005Q1 to 2016Q4. The dynamic factor technique is used to detect co-movements and common patterns and well as the relationship between default rate and exploratory factors, using the SPSS. The factors went through normalization, extraction, determination and rotation. Complementary econometric tests include: a unit root test to determine its stationarity. The Vector Error Correction Model was equally done, with special emphasis and focus on the short run dynamics of the factors. We equally applied the Granger Causality test in order to determine existence of causality. The factor analysis results empirically revealed that the business cycle factor is positively related with default rate, though not statistically significant at 5% but it accounted for 46.948% variability of the default rate. Macroeconomic factor accounted for 17.662 variability which is statistically significant. Inflation singlehandedly cued under Price Indication factor at 14.379% variability though not statistically significant. Therefore, we recommend: creation of capital buffers beyond the minimum requirements needed during economic booms in order to tackle procyclical effects prescribed in Basel II. This is a way to help enshrine financial stability in the banking system. Contemporary macroeconomic issues should be incorporated in modeling credit risk to enhance financial stability and as well cushion against increase in bankruptcies. Lastly, to abate corporate defaults, lending policies of financial in Nigeria institutions should reflect the dynamics of inflation and its associated pressures it cause the Nigerian economy

Keywords: Dynamic Factor Analysis, Default Rate, Business Cycle, Macroeconomy, Portfolio Credit Risk.

INTRODUCTION
The occurrence of 2007-2008 global financial crisis and the subsequent escalation of default rates have propelled avalanche of studies on better ways of managing portfolio credit risk of financial institution. After the global financial turbulence, a plethora of banks in the United States of America collapsed, which spiraled numerous bank failures in other parts of the world. Consequently, the global financial crises amplified the prominence of credit risk (default) as a major risk faced by financial institutions which are commonly tied with loans and advances in banks’ balance sheet. Evidently, studies have equally shown that credit risk is major the cause of bank failures and as well the most conspicuous risk faced by bank management (Fraser et al, 2001). In affirmation (Jakubik, 2007) assets that credit risk is undoubtedly one of the main components of risk management that is of great relevance for financial institutions
Therefore, it is imperative that adopting better credit risk assessment models in predicting corporate defaults is absolutely essential for sound and resilient financial and economic systems. In other words, the more or near exactness or accurate researchers can become in predicting the probability of default, the harder or rarely it will be for economies to be hit by any sudden financial panics or meltdown as that of 2007/2008, (Senkoto, 2012).

Essentially, avoiding corporate failures arising from credit defaults, financial institutions are deeply motivated to developing sound credit risk models that are quantitatively based as prescribed by the Basel II. Also, (Jakubik (2007) asserts that credit risk is undoubtedly one of the main components of risk management that is of great relevance to financial institutions. This sense of relevance has made banking institutions to develop their own credit risk models with the aim of enhancing portfolio quality, which was emboldened by the introduction of the new based capital accord, commonly known as Basel II. As emboldened by the Basel II. The ability to accurately predict the probability of default vis-à-vis the implication for portfolio credit risk modeling in the Nigerian banking industry could be made smoother through the applicability of dynamic factor analysis which this study opts to adopt.

Chieflly, the dynamic factor model is used in the analysis of co-movements in bank risk portfolios. Similarly, (Stock & Waton, 2009; Forni et al, 2000, 2002; Gropp et al, 2002, 2001) prescribe that the dynamic factor model allows banks to measure co-movements in credit risk portfolios through the applicability of distance-to-default as an indicator of fragility. Equally, (Nickell and Perrandi, (1999) and Lehar (2003) affirmed that the applicability of the dynamic factor model in banking institutions assist banks drive default probabilities from the observable market data premised on the Option Pricing Theory. To them it will aid the computation of risk simultaneous weakness of banks as well as consider assets return correlations.

Specifically, this study opts for dynamic factor models due the tremendous attention it had received over a decade and now. The DFM has the ability to model simultaneously and consistently data sets which number series that surpass the number of observations. The DFM was initially applied by (Geweke, 1977). While, Sergeant and Sims (1977) extended to two factor models. Other notable scholars like Bai and Ng (2008) and Stock and Watson (2006) have done complimentary studies using this model.

Back to the Nigerian scenario, the USA sub-prime crises led by the global financial pandemonium of 2007-2008, which crept into Nigeria, visibly led the economy into recession. The banking sector was badly hit by the global happenings resulting in collapse by 70% of The Nigeria Stock market While many Nigeria banks were rescued by the injected N620bn by Central Bank of Nigeria to boost liquidity and as well improved corporate governance standards of Nigeria banks. According to Sanusi (2010) this externally provoked financial panic had caused the quality of banks credit portfolio to deteriorate. To large extent, equity market indices, global oil prices nose-dived. The Nigeria economy was adversely affected as banks could not spread credit to businesses (Kolapo; Ayeni & Oke, 2012)

In support of the above, Ahmad and Ariff (2007) assert that most banks in other developed and developing economics such as Thailand, Indonesian, Malaysia Japan and Mexico encountered rise of non-performing credit portfolios as well as proportionate increase in credit risk during the crises period which caused some bank failures. In response to this financial meltdown and due to the limitation of Basel I in capturing the broader risk exposures of banking institutions financial regulators launched a robust agenda for reform of the global financial architectural framework, the Basel II, to broadly sustain the minimum capital requirements as well as adopt more advanced credit risk measurement and management technique in evidence of the above.

Clearly, apart from re-capitalizing the banks to withstand domestic and global economic shocks, the Central Bank of Nigeria has instituted several initiatives/policies that led to the compliance of Basel II. Evidently, the global financial cracks propelled the Federal Government to propose the Asset Management Corporation of Nigeria (AMCON) bill which was enacted into law as an act in July 2010 by the National Assembly the AMCOM Act seeks to ensure financial system stability by effectively resolving the non-performing loan assets of Nigerian banks.

Pertaining to the relevance of this study, there are several reasons that motivate the researchers in embarking on this study. First, it will help financial practitioners and regulators on better ways to manage
deteriorating quality of credit portfolio, through the thorough grasp on how to precisely estimate/predict probability or default in every loan or corporate bond portfolios, bearing in mind its effects financial institutions/economic stability. Second, the study will help financial practitioners and regulations to understand how the likely rate of default may arise due shocks that associated with macroeconomic dynamics and business cycle movements. Third, it will help banks in developing stress tests of their portfolios during business cycle downturn and properly situate the interpretations underlying the shocks. In this way, an advance action will be taken to avoid the default, which is highly encouraged by the Basel II
The scope of the study is based on 2005Q1 to 2016Q4. The central objective of this research is to empirically model macroeconomic and business cycle variables on default rates in the Nigerian Banking Industry. Whereas, other specific objectives are: to establish if a relationship exist between default rates and business cycle factor; to find out the type relationship between default rates and macroeconomic factor.
Pursuant to the research objectives, the following are the research questions this study seeks to answer are: Is there a relationship between default rates and business cycle factor? Is there a relationship between default rates and macroeconomic factor?
The leading hypotheses in the study of dynamic factor analysis of default rates and portfolio credit risk modeling in Nigerian banking industry are hereunder stated: there is no relationship between default rates and business cycle factor; there is no relationship between default rates and macroeconomic factor.
The Problem that motivated this research is: The escalation of defaults vis-a-vis bad /non-performing loans and advances of banks in Nigeria is threatening its soundness and stability as well as mimicking the efforts of practitioners and regulators. This phenomenon is aggravated as a result of inappropriate/un-robust credit risk methodologies and use of accounting models that cannot factor variables relating to macroeconomic and business cycle in estimating probability of default of credit portfolio.
Evidently, according to CBN report (2016) Non-performing loans of banks went high by 78% year-on-year to N649, 63billion in 2015, which is far beyond the global average of 5% annual increase of non-performing loans. This no doubt has led rating agencies, in the likes of Fitch and Moody’s to downgrade the credit ratings of large Nigerian banks because of the alarming rate of non-performing loans. Hence, the problem scenario chronicled above provides us the opportunity to study modeling of default rates on macroeconomic and business cycle dynamics in the Nigerian Banking industry. The researchers believe, this study will help provide answers to ameliorate default risk and as well as improve the quality of credit portfolio.
In conclusion, this paper is structured into introduction, theoretical framework, literature review, research methodology, results, conclusion and recommendation.

Theoretical Framework
The theoretical framework of this research work is anchored on the Options Pricing Theory and the Cash Flow Theory of Default. The Options Pricing Theory, amplified by the works of Black and Scholes (1973) and Merton (1974) stipulates that firms are to be financed with equity and debt claims, and both are held by one representative agent with a time-addictive power utility function. Implying that default probabilities are assessed from the structural relationship between equity, debt and asset value, default is considered as an event after which a firm could not fulfil it commitment as a result of financial loses of security holders, default is a rare event that once it happens it will have significant financial loses and that default is predicted with a certain degree of probability.
The second is the Cash Flow Theory of default. This incorporates systematic factors in capturing the economy, and is based on the intuition that default event occurs when the borrower incurs negative cash flows; The borrower’s credit worthiness is increasing as net cash income, credit reserves or available credit increases, but is decreasing, as the amount of the periodic loan obligations increase and that loan portfolio has a significantly large number of exposures, each exposure is homogenous and identical in size. And that default event occurs independently conditional on the realization of systematic factors.

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However, Kim (2005); Scott (1981); Zeitun, Tian and Keen (2007) applied this theory in investigating the effect of cash flow on corporate default.

**Conceptual Framework of Dynamic Factor Model**

The dynamic factor model is used in the analysis of co-movement of banks risk. Principally, co-movements in financial institution risk happen as a result of nakedness to common shocks, which may erupt from various sources. According to Upper and Worms (2000), Gropp and Vesala, (2004) and Brasili and Valpes (2005), the common shocks may be akin to macroeconomic, business cycle, stock market, banking, labour market, industries, countries, individual actions. Typically, co-movements in financial institutions fragility portend clear dangers with regard to systematic stability, which are most frequently attributable to events of banking failures. This has far reaching policy implications on the part of regulatory banking authorities in carry out banking supervisory duties globally. Most times such financial fragility happens due macroeconomic shocks, in other times, it occurs due other system specific factors from business cycle, industry, etc. However, establishing a measure of co-movements in bank risk using the dynamic factor model would allow us to identify the bank fragility indicator. Evidently, Brasili and Valpes (2005) used the dynamic factor model approach to analyze co-movement in the fragility of European Union financial institutions. Their result showed that the fragility of banks is partly related to macroeconomic shocks.

In support of the above, other notable scholars that have applied the dynamic factor model such as Stock and Watson (1999); Forni et al, 2000, 2002 & Gropp et al, 2002, 2001) affirm that the dynamic factor model permit banks to measure co-movements in credit risk portfolios through the applicability of Distance-to-Default (DD) as an indicator of fragility.

Similarly, Nickell and Perrandi (1999) and Lehar (2003) confined that the applicability of the dynamic factor model in banking institutions helps banks to examine fragility on credit portfolios and largely help banks drive default probabilities from the observable market data premised on the option proving theory. This they concluded will aid the computation of risk of simultaneous weakness of banks by taking into consideration assets return correlations.

Truly, Dynamic Factor Model (DFM) has received tremendous attention over a decade and now. This is due to its ability to model simultaneously and consistently data sets which number of series surpass the number of observations. The DFM was initially applied by (Geweke, 1977). While study Sargent and Sims (1977) extended to two factor models. Other scholars Bai and Ng (2008) and Stock and Watson (2006) have complimentary studies using this model.

The bases of a DFM is achieved on the premise that a few latent dynamic factors, $f_t$ instigate or propel the co-movements of a high - dimensional vector of series variable, $x_t$, which is also hampered by a vector of mean – zero idiosyncratic disturbance, $e_t$. Apparently, these idiosyncratic disturbances occur from measurement error and from special features specific to individual series.

The latent factor take after a time series process, commonly regarded to a Vector Auto Regression (VAR). The equation of the DFM is

$$X_t = \lambda(L) F_t + \ell_t$$  \hspace{1cm} (1)

$$F_t = Y(L) f_{t-1} + \eta_t$$  \hspace{1cm} (2) Given

that: there are N series, $X_t$ and $e_t$ are N x 1,

There are q dynamic factors $s_q, f_i$ and nL are q + 1,

$L$ is a log operator, hence the Lag polynomial matrices (L) are N x q and q x q respectively.

The $i^{th}$ lag polynomial $\lambda(L)$ is known as the dynamic factor loading given $i^{th}$ series, and $\lambda_i(L)f_t$ is the common component of the $i^{th}$ series.

Normally, the dynamic factor model has three assumptions. First it assumes that equations 1 and 2 are stationary. The second assumption is that the idiosyncratic disturbance are assumed to be uncorrelated with the factor innovations at every lead and lag, $E e_i \eta_{t-k} = 0$ for all K. The third holds that the idiosyncratic disturbance are assumed to be naturally uncorrelated at every level and lag, $E e_{it} e_{jt} = 0$ for all K.
Another vital reason for utilizing DFMs is that having known the factors $f_i$ and if $(\ell, \Pi)$ are Gaussian. Then the coefficient of the individual variables using the population regression can be made. In other words, the $N$ variables by using factors, given that is smaller than under squared error loss is the optimal one – step ahead forecast of the $i^{th}$ variable is

$$E[X_{i+1}|X_i, f_i, X_{i-1}, f_{i-1}, \ldots]$$

$$= E[\lambda_i (L) F_{i+1}/ X_i, f_i, X_{i-1}, f_{i-1}, \ldots] + E[e_{i+1}/X_i, f_i, X_{i-1}, f_{i-1}, \ldots]$$

$$= E[\lambda_i (L) F_{i+1}/ X_i, f_i, X_{i-1}, f_{i-1}, \ldots] + E[f_{i+1}/e_i, e_{i-1}, \ldots]$$

$$= E[f_{i+1}/e_i, e_{i-1}, \ldots] + E[\lambda_i (L) F_{i+1}/ X_i, f_i, X_{i-1}, f_{i-1}, \ldots]$$

$$= \alpha (L) F_i + \delta (L) X_i$$

### Empirical Evidence

#### Default Rate and Macro Economic Factors

The relevance of macroeconomic variables on firm’s corporate profitability is adjudged to be too vital for neglect. It is therefore logical to take macroeconomic factors into consideration when assessing the risk profile of corporate organization. This therefore, makes default probability analysis a matter of importance particularly as it relates to macroeconomic fluctuations. The following literates indicate in many ways that macroeconomic factors play a vital role in the prediction of probability of corporate defaults. Hence, the vitalness of these variables is predicting default rate is found in both structural and reduced models.

Nilsson and Laurin (2009) carried out a study on the influence of macroeconomic variables on the probability of default in Sweden, using the panel data analysis in their study, two different panel models for large firms and the medium and small firms, all Swedish non financial firms were employed. In their regression model, the distance to default was the dependent variable while the macroeconomic factors were the independent variables. In arriving at the distance to default of firms, the Moody’s KMV model was utilized; their empirical findings revealed that one year lagged macroeconomic variables explain 75% of the changes to the probability of default of the of the sample firms.

Qu (2000) mainly adopted the methodology of Wilson (1997) who asserted that a non-dynamic systematic factor model is not adequate to enough to represent all systematic variables that will be used to estimate probability or default. Hence, Qu looks at the nexus between probability of default on one hand and industrial production, inflation, interest rate, share price exchange rate unemployment on the other hand. Qu further carried out analysis for dissimilar industries and geographical areas to ensure robustness. Empirically, Qu finds as expected the impact of macroeconomic factors on the probability of default changes with countries and exhibit very strong impact on default probability.

Koopman et al (2009) assert in their research of default probability and macroeconomic factors which they relate probability of default and rating cycles (business cycle, bank lending cycle and financial market indicators). Their studies empirically demonstrated the harsh and confronting persistence of macroeconomic factors (GDP growth rate, interest rate and stock market indicators). They further found that the addition of an undesirable dynamic factor to the model which already harbours an observable systematic risk element, the explanatory power of the model heightens.

Jimenez and Mencia (2009) carried out a research pertaining to probability of default of aggregate credit portfolio of the Spain banking system. They empirically found the perseverance of latent factor, aside the macroeconomic factors in the model. They further concluded that the latent factor propels the strength of the relationship existing between credit default and macroeconomic variables. Typically, they establish that event or exposures of defaults are higher during times of economic recessions than times of boom.

Shahnazarian and Sommar (2008) use the vector error correction model to research on the connection between average expected default rate frequency, and macroeconomic factors. Their study is meant to give credence to the stability analysis of risky banks in the Sweden. They apply the Moody’s KMV model. The expected default frequency represents the event of default is the dependent variable. While macroeconomic factors like inflation, manufacturing output index and interest rates stand as undependable variables. Their study empirically shows that manufacturing output index propels lower
default. Rising inflation short-term interest rates propel negative influence on the average default frequencies.

Rolwes and Simons (2008) study the nexus between the default probability of Dutch firms and the macroeconomy using the logit model. The researchers consider the logit model to tackle the cons of macroeconomic risk model of short-period span, bearing in mind that the data is shorter than the business. Their study spans from 1983 to 2006, and they empirically found that a higher-level nexus exist between GDP growth rate and oil prices with the default probability but a less fierce connection with interest and exchange rates. Also, the first lag of the probability of default shows an extremely notable coefficient meaning that the effect of tenacious macroeconomic shocks rises over a long period.

Jakubik (2009) studied the macroeconomic environment and credit risk, using the Merton’s approach to structural analysis in modeling default rates. With the introduction of a latent factor in making clarity with respect to understanding the relationship existing between credit risk and macroeconomic indicators, the applicable model found a very strong nexus between bank portfolio quality and the macroeconomic environment.

Lamb and Perrandin (2008) in their work on dynamic default rates, they developed latest, dynamic and conditional versions of Vasicek’s single factor model and default rate distribution. New group of distributions in modeling US banks loan losses were adopted. Fundamentally the effects for risk, capital, diversification and cyclical effects in loan portfolios and further investigated on how certain macroeconomic factors like industrial production shocks and unemployment hamper on credit losses distribution. Finally, the result showed that the risk characteristics and general behaviour of losses in a conditional and unconditional state are quite divergent.

Senkoto (2012) investigated macroeconomic variables underlying synchronization in probabilities of default particularly of South African firms. Specifically, the relationship between macroeconomic variables and default probabilities were studied. Data of 8 south African firms were analyzed from January 1997 to December, 2010, by employing the Kealhefer, Merton and Vasicek (KMV) model to econometrically estimate the probabilities of default using dynamic factor model (DFM) to establish synchronization and the extend which common factors drive probabilities of default. Thereafter, the result of the investigation showed that probabilities of South African firms are synchronized to a certain measure as allowed by the economic environment. Fundamentally, the dependency of defaults on these economic variables is tied to firms’ policies, they concluded.

**Default Rate and Business Cycle Factors**

Jhingan (2011) sees business cycles as the cyclical fluctuation of expansion and contraction of the Gross Domestic product GDP. These fluctuations are characterized with cyclical wave-like movements that are recurrent in nature. Typically business cycle has four phases namely: expansion recession, contraction and recovery. Fundamentally, business cycles are normally measured using the growth rate of real gross domestic product. In essence these fluctuations in economic activities are seen unpredictable.

On the other hand, financial fragility is the susceptibility of the financial system to financial distress or panics. Also, Allen and Gale (2002) reveals that mainly, there are two views of financial fragility or banking crises. The first one considers the happening of financial panics due spontaneous events that are not connected the changes in the real economy. The researches of Kindleberger (1978) and Diamond and Dybvig, 1983) support the firs view.

Alternatively, the works of Gorton (1988) Calomires and Gorton (1991) Calomiris and Mason (2000) back the second view. They commonly opined that financial fragility happen as a result of natural outgrowth of the business cycle. Invariably, an economic depression or downturn will lower the value of bank assets and as well exposed to the inability of meeting commitments.

According to Allen and Gale (2012) the first school of thought of financial fragility holds that stochastic fluctuations in the economy are causal by intrinsic uncertainty while the second holds that economic dislocations are caused by extrinsic uncertainty.

In respective of the opinion of any school of thought, there appear to be a common stance – uncertainties can trigger financial panics and the financial system is naturally fragile. However, the peril of any
financial crisis centers on the level of damage it will render the economy. In the light of the above, the following works are examined.

Allen and Hale (2012) in their study on financial fragility looked at the relationship between fundamental equilibrium and sunspot equilibrium in the light or current financial panics and found that there are numerous sunspot equilibrium and only a fee are the level of fundamental equilibrium at the instance that exogenous fundamental uncertainty diminishes. Further, they demonstrated that under peculiar conditions only robust or large equilibrium are those that instigate extrinsic uncertainty that eventually birth financial panics with positive probability.

Facchini (2015) in studying financial fragility and central bank in Austria using the Minsky’s post-Keynesian theory found that financial fragility or markets with respect to the central bank in discharging one of its functions as a lender of last resort will escalate risk and would rather not cause financial panics. Rather the organized capitalism instigates market instability and eventually financial fragility.

Allen (2005) postulates that financial fragility can offer huge consequences on an economy. And that asset price bubbles is an economy. And that asset price bubbles have three peculiar stages. The first stage begins with financial liberalization or a thoughtful decision by the regulatory/central bank to escalate lending or other related monetary actions. This will lead an expansion in credit associated with a relative increase in prices of assets like real estate and stocks. In the second stage, the bubble bursts and eventually asset prices fall, this happens over a four period not more than days or months and rarely takes longer. The third stage is largely associated with default of huge proportion of firms who borrowed to purchase assets at persistently increase prices. Eventually this gale of defaults will propel banking and foreign exchange panics. Broadly, the troubles emanating from defaults, banking and foreign exchange instability in most instances instigate troubles in the real sector of the economy which in most cases these crises last longer.

Bruno, Cartapins and Nasica (2013) examined bank leverage, financial fragility and parametrical regulation. They analyzed the key elements of financial institutions balance sheet and leverage ratio dynamics and their associated role in rising financial fragility. The results were in two strands. First strand showed that there is a value of financial institutions leverage that reduces financial fragility. The seconds stand reflected that leverage value rely on the larger business climate, the expected collateral value and the riskless nature of interest rate. Based on their result, they further advocated for the setting up of an adjustable leverage ratio, that will be premised an economic conditions, rather that the usually fixed ratio provided for in the Basel II regulation.

**METHODOLOGY**

In this study, we adopted the qualitative approach to test casual hypothesis, it involves selecting groups based on certain characteristics/trait and testing of variables without any randomization and selection process. The different groups are analyzed and compared to in regards to independent and dependent variables. The assignment of variables is based on the interest of the researcher. According to White and Subarwal, 2014; David and Lemieux, 2009, the results are generated upon comparison of variables of different groups over a period of time and compared with similar trends. It patterns after a quantitative experiment, especially advanced statistical and econometric tools which will internally address selection bias.

The entire commercial banking industry (as published by The Central Bank of Nigeria) served as the population of the study. Sample size was not determined because we considered 100% of the population. The quasi-experimental research design adopted gives no room for the use of a particular sampling technique.

Essentially, this study relied heavily on secondary data. As we made progress, data on non-performing loans and advances will be sourced from Nigeria Deposit and insurance Corporation (NDIC) for the period covering 2005Q1 to 2016Q4. In line with the Central Bank of Nigeria revised Prudential Guidelines, non-performing loans are grouped into: Substandard (overdue > 90 days); Doubtful (180-360
The default rate will be calculated by the fraction of non-performing loans and advances to total loans and advances.

\[ \text{Default Rate}_{i,t} = \frac{\text{Non-performing loans and advances}_{i,t}}{\text{Total Loans and Advances}_{i,t}} \times 100\% \]  

This formula is in consistent with the Basel II definition of default. However, Jakubik (2007) also adopted this methodology in determining default rate. With respect to data on macroeconomic, business cycle and price indicator variables such as GDP growth rate, exchange rate, index of industrial production, GDP per capita, Index of agric production and inflation rate, we obtained from Central Bank of Nigeria (CBN) Statistical Bulletins and Nigerian Bureau of Statistics Reports & Publications for the period 2005Q1 to 2016Q4.

**Dynamic Factor Model Specification**

Following after the works of Geweke (1977), Sargent and Sims (1977) and Stock and Watson (2002), the researchers structured the dynamic factor model with slight modifications with regards to increase in number of factors. However, the principal logic behind the DFM is that the observation 't' of a data set can be modeled as the sum of a number of common factors together with the lags of common factors as well as the idiosyncratic term (et)

\[ y_{i,t} = a_i + b_1 f_t + e_{i,t} \]  

Where:

- \( y_{i,t} \) = dynamic observables; \( a_i \) = constant; \( b_i \) = exposure or Loading; \( i = \) series to the common factors; \( f_t \) = factors

Therefore, from the above equation we allow both factors and the idiosyncratic components to follow an Autoregressive process

\[ Y_{dr} = a + b_1 f_{i-1} + b_2 f_{i-2} + b_3 f_{i-3} + e_{i-1} \]  

Where, \( Y_{dr} \) represents a ratio of NPL to Total Loans granted by Commercial Banks in Nigeria; \( f^m \) is for Macroeconomic Factor; \( f^bc \) stands for Business Cycle Factor; \( f^p \) represents Price Indicator Factors; \( b_{1-5} \) are respective factor loadings. Pertaining to its Assumptions, the model postulates that all co-movement in the dataset happens from the factors and that factors are assumed to be uncorrelated with one another.

**Dynamic Factor Analysis**

Specifically, factor analysis in this study, it is used to model portfolio credit default in the Nigerian Banking Industry. Several variables that propelled default rate are categorized in to factors (dimensions) and analyzed using the SPSS. The factors are used to explain their relationship with default rate upon normalization, determination, extraction and rotation. In this study we adopted: the principal component normalization, factors were extracted through the Principal Component Method, the Kaiser Criterion was used in determining the number of factors. The factors were rotated through a process of manipulation or adjusting factor axis to achieve a simple and pragmatic more meaningful factor solution through Varimax.

**Complementary Econometric Analysis Tests**

**Unit Root Test** In this study, we adopted the panel unit root test procedure described by Bai and Ng (2004), as PANIC, Panel Analysis of Non-stationarity in Idiosyncratic and Common components. It tests for unit roots in the common factors and or the idiosyncratic factors. In testing for Granger causality the researchers followed after (Granger (1969) and Hossian and Jashim (2017) to study the directions of the relationship between the factors in applying the granger causality test. The simplest form of the granger causality test can be performed using the following equation

\[ Y_t = \alpha_0 + \alpha_1 F_{t,1} + \alpha_2 F_{t,2} + \ldots + \alpha_k F_{t,k} + \beta_1 Y_{t,1} + \beta_2 Y_{t,2} + \ldots + \beta_k Y_{t,k} + \mu \]  

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Jakubik (2007) upon applying dynamic factor analysis which by default takes into cognizance the existence of long run relationship in the model used the Vector Error Correction Model to distinguish long-term and short–term dependence. Therefore, in this study we placed emphasis on establishing only the short run relationship by adopting the VECM. The VECM is a restricted VAR applied to nonstationary series that has a cointegration relationship, by design it restricts the long-run behaviour variables to converge to their cointegration relationships while allowing for short run adjustments dynamics. In applying this statistical tool, our emphasis is placed on the short relationship.

RESULTS
Dynamic Factor Descriptive Statistics
The table below simply shows the means, standard deviations and number of observations (analysis N). The average score of all the variables are not similar. The predictive variable, DR, has the lowest mean of 3.0206 while the GPC has the highest mean of 2155.0167. The standard which is a measure of the spread, records a lowest value of GRR at 3.36907, while the IAP holds the highest spread of 1579.28877.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Analysis N</th>
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<tbody>
<tr>
<td>DR</td>
<td>3.0206</td>
<td>3.80931</td>
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<td>ER</td>
<td>157.4854</td>
<td>44.19994</td>
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<td>INF</td>
<td>11.0856</td>
<td>4.55302</td>
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<td>GRR</td>
<td>5.4477</td>
<td>3.36907</td>
<td>48</td>
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<td>IIP</td>
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<td>GPC</td>
<td>2155.0167</td>
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<tr>
<td>IAP</td>
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</table>

Test for Sphericity and Sampling Adequacy
The above will be done through the Kaiser-Meyer-Olkin and Bartlett’s test. Bartlett’s test measures Sphericity, implying that the condition where the variances of the differences between all possible pairs of within levels of the independent variables are equal. It compares the correlation matrix with a matrix of zero correlations, technically known as the identity matrix, consisting of all 0’s and 1’s along the diagonal. While the KMO Measure of Sampling Adequacy, when it is below 0.5, it is considered poor while above 0.5; preferably above 0.6 is taken as a properly correlated identity matrix. Invariably, this implies that the problems of multicollinearity have been eliminated. The significance of 0.000 indicates that the model is properly fitted and that the factors with load perfectly. The p-value is less than 0.001 which is normal but by default SPSS reports p-values less than 0.001 as 0.000. The Approx. Chi-Square statistic measures the adequacy of the number of observations (N), values above 220 are said to be normal, however, ours is 183.615 which is slightly lower but has a significant adequacy regarding number of observations.

Communalities
From the table 3, the associated communalities represent the total influence of the observed variables possess on predictive. This statistic is akin to the sum of the entire squared factor loading to the observed variable, which is the same as $R^2$ in multiple regressions. Simply, the decision criterion implies that
extracted communality values range from 0 to 1, where towards 1 indicates that the variable is fully defined by the factors. In contracts, values tending towards 0 indicate that the variable cannot be predicted from any of the factors.

As typically shown in the table 3 the predictive factor, DR, has a communality extraction of 0.651 while the other explanatory variables have shown very high communality extractions of 0.700 for ER; 0.970 for INF; 0.915 for IPP; 0.895 for GPC; 0.804 for IAP which are very close to 1, meaning that the observed variables are fully defined by the factors.

**Table 3 : Communalities**

<table>
<thead>
<tr>
<th></th>
<th>Initial</th>
<th>Extraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>DR</td>
<td>1.000</td>
<td>.651</td>
</tr>
<tr>
<td>ER</td>
<td>1.000</td>
<td>.700</td>
</tr>
<tr>
<td>INF</td>
<td>1.000</td>
<td>.970</td>
</tr>
<tr>
<td>GRR</td>
<td>1.000</td>
<td>.594</td>
</tr>
<tr>
<td>IIP</td>
<td>1.000</td>
<td>.915</td>
</tr>
<tr>
<td>GPC</td>
<td>1.000</td>
<td>.896</td>
</tr>
<tr>
<td>IAP</td>
<td>1.000</td>
<td>.804</td>
</tr>
</tbody>
</table>

SPSS Version 21 Output.

**Total Variance**

This explains how much of the variability in the data that has been modelled by the extracted factors.

From the Variance Table 4 below three (3) Factors/components with Eigen value greater than 1.00 explain 78.988% of the cumulative variability in the data. This leads to the conclusion that a three-factor solution will be ideal for the study.

In details, Factor 1 accounts for 46.948% of the variability, Factor 2 harbours 17.662%, Factor 3 holds 14.379%.

**Table 4: Total Variance Explained**

<table>
<thead>
<tr>
<th>Component</th>
<th>Initial Eigenvalues</th>
<th>Extraction Sums of Squared Loadings</th>
<th>Rotation Sums of Squared Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>% of Variance</td>
<td>Cumulative %</td>
</tr>
<tr>
<td>1</td>
<td>3.286</td>
<td>46.948</td>
<td>46.948</td>
</tr>
<tr>
<td>2</td>
<td>1.236</td>
<td>17.662</td>
<td>64.610</td>
</tr>
<tr>
<td>3</td>
<td>1.006</td>
<td>14.379</td>
<td>78.988</td>
</tr>
<tr>
<td>4</td>
<td>.787</td>
<td>11.246</td>
<td>90.235</td>
</tr>
<tr>
<td>5</td>
<td>.362</td>
<td>5.173</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>.274</td>
<td>3.914</td>
<td>95.408</td>
</tr>
<tr>
<td>7</td>
<td>.047</td>
<td>.678</td>
<td>100.000</td>
</tr>
</tbody>
</table>

Extraction Method: Principal Component Analysis.

SPSS Version 21 Output.

**Scree Plot**

Apart from using the Eigen value of greater than 1, the screen plot help show out where the factors leveled off. Following the factor analysis carried out using the Principal Component Analysis method. The above screen plot determines that three factors are all above the Eigen value of 1 on the graph, which
indicates that the factors are properly extracted and as well adequate to model the dynamics of default rate on the factors.

![Scree Plot]

**SPSS Version 21 Output.**

**Figure 1: Scree Plot**

**Factor Loadings**

Factors were extracted using the Principal Component Analysis (to aid in the extraction of uncorrelated linear combination of variables) and rotated through the Varimax with Kaiser Normalization to help simplify the factors; the rotation converged in 4 iterations. The Principal Component criterion is applied in choosing the number of variables under the five various factors. All adequately have a component score coefficient above 0.05%.

From the rotated component matrix table (see table 5). The variables under study conveniently loaded/extracted under the five factors. As typical of dynamic factor analysis, the predictive variable is the first component while the proceeding components are the explanatory variables. Hence, the predictive component, DR helps indicate a positive or negative relationship with other variables. As a general rule of thumb, only variables with the highest positive loading will be selected as the respective factor variables. Originally, it was expected that the six explanatory variables under study will conveniently and evenly load under macroeconomic, business cycle factors, given their idiosyncratic/individualistic latent characteristics. However, upon carrying out the rotated component matrix, it was found that exchange rate shifted from macroeconomic to cue behind business cycle factor, while inflation moved away from macroeconomic to assume price changes indicator. While only GRR cued behind macroeconomic factor. This dynamics caused realignment of explanatory variables along their idiosyncratic traits. The latent combinations are shown below and the component plot in rotated space figure:

**Table 5: Rotated Component Matrix**

<table>
<thead>
<tr>
<th></th>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>DFRC</td>
<td>.269</td>
<td>.759</td>
<td>.054</td>
<td></td>
</tr>
<tr>
<td>ER</td>
<td>.785</td>
<td>.054</td>
<td>.285</td>
<td></td>
</tr>
<tr>
<td>INF</td>
<td>.047</td>
<td>.044</td>
<td>.983</td>
<td></td>
</tr>
<tr>
<td>GRR</td>
<td>-.291</td>
<td>.713</td>
<td>.005</td>
<td></td>
</tr>
<tr>
<td>IIP</td>
<td>.955</td>
<td>-.027</td>
<td>-.041</td>
<td></td>
</tr>
<tr>
<td>GPC</td>
<td>.926</td>
<td>.181</td>
<td>-.078</td>
<td></td>
</tr>
<tr>
<td>IAP</td>
<td>.848</td>
<td>-.287</td>
<td>.053</td>
<td></td>
</tr>
</tbody>
</table>
Factor Identification and Relationship with Default Rate

Factor 1 is identified as Business Cycle Factor (BCF). The highest positive loadings are 0.785, 0.955, 0.926, 0.848 respectively corresponding to ER, IIP, GPC and IAP. The lead indicator is GPC, which is an indicator of business cycle. Other variables following the GPC seem to possess similar latent factors that depicts why they queue behind the lead variable.

Therefore, Factor 1 has an overall variability of 46.948% and is positively related with the predictive variable, Default Rate, though not significant at 5%. In other words, each of the variables loaded under factor 1 has a positive relationship with the dependent variable, which is simply indicating a direct relationship. Implying that an increase in explanatory variables will lead to increase on predictive and vice versa.

Factor 2 is identified as Macroeconomic Factor (MF). It has idiosyncratic characteristics of the Macroeconomy harbouring only GRR with positive factor loading of 0.713. Hence, it is called Macroeconomic Factor. Its variability of 17.662% is significant at 5%. It has a positive relationship with the predictive variable. This relationship is not expected but it is in line with economic theory. Scholars are linking loan portfolio credit with macroeconomic factor. Their studies establish that default risk tends to rise during economic downturns. However, banks with higher exposures to macroeconomic risks are expected to have higher non-performing loans.

Factor 3 is known as Price Indicator Factor (PIF). It has latent trait that tends towards price indicator. Hence it is labeled Price indicator Factor. It accounts for 14.379% variability, and has a positive relationship with the predictive variable, default rate. Though not Significant at 5% level.

Table 6 Factor Identification

<table>
<thead>
<tr>
<th>Factor</th>
<th>Variables</th>
<th>Load</th>
<th>Lead Variable</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor 1 (Business Cycle Factor)</td>
<td>Index of Industrial Production</td>
<td>0.955</td>
<td>This factor is called Business Cycle Factor because the lead variable IIP has related business cycles latent traits.</td>
<td>IIP</td>
</tr>
<tr>
<td></td>
<td>GDP Per Capita</td>
<td>0.926</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Index of Agri. Production Exchange Rate</td>
<td>0.848</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Exchange Rate</td>
<td>0.785</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor 2(Macroeconomic Factor)</td>
<td>GDP Growth Rate</td>
<td>0.713</td>
<td>This factor is called Macroeconomic Factor because the lead variable GRR shows related latent traits.</td>
<td>GRR</td>
</tr>
<tr>
<td>Factor 3(Price Indicator Factor)</td>
<td>Inflation</td>
<td>0.983</td>
<td>This factor is called Price Indicator Factor because the lead variable INF has related latent traits.</td>
<td>INF</td>
</tr>
</tbody>
</table>

Source: Authors’ Compilation
**Test for the Significance of the Factor Loadings (Hypotheses)**

According to Koutsoyiannis (1977), the test for significance of the factor loadings in Principal Component Analysis is done based on the levels of significance of the Pearson correlation coefficients, as it is assumed that the loadings are in effect similar to the correlation coefficients. There are critical values for the significance of the Pearson Product Coefficients for different sample sizes (number of observations). These critical values are the standard errors of the Pearson Product Coefficients. The number of observations of this study is 48. If the value of predictive variable at 5% level of significance is greater than ± 0.280 then it is statistically significant. On the contrary, it will be regarded as statistically insignificant.

<table>
<thead>
<tr>
<th>Table 7: Hypotheses Testing of Factor Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor</td>
</tr>
<tr>
<td>Rotated Component Matrix of the Predictive Value (DR)</td>
</tr>
<tr>
<td>Test of Significance at 5% (significant if DR is &gt;± 0.280)</td>
</tr>
<tr>
<td>Statistically Not Significant, DR&lt;± 0.280</td>
</tr>
<tr>
<td>Statistically Significant, DR&gt;± 0.280</td>
</tr>
<tr>
<td>Statistically Not Significant, DR&gt;± 0.280</td>
</tr>
<tr>
<td>0.269</td>
</tr>
</tbody>
</table>

From the above table, the following hypotheses are summarized:
There is no significant relationship between Default Rate and Business Cycle Factor. However, the relationship is positive; the relationship between Default Rate and Macroeconomic Factor is positive and statistically significant; there is no significant relationship between Default Rate and Price Indicator Factor. However, the relationship is positive.

**Econometrics Result Analyses**
We applied econometric analyses, principally to establish if there exist stationarity problems, causality and short run (using the Vector Error Correction Model) relationships.

**Analysis of Estimation Results**
An econometric estimation is done to establish the Relationship between Default Rate (DR), Business Cycle Factor (BCF), Macroeconomic Factor (MF) and Price Indicator Factor (PIF).

**Stationarity Analysis between DR, BCF, MF and PIF**
The table below depicts the results of the Augmented Dickey-Fuller (ADF) unit root of the predictive variable and factors: BCF, DR, MF, PIF. The results show that all the variables were not stationary at level but became stationary after first difference at 5% significance level, implying that they are all integrated or stationary at second level $I(2)$. Therefore, we reject the hypothesis of no stationarity in all the variables.

<table>
<thead>
<tr>
<th>Table 8: Factor Unit Root Test Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
</tr>
<tr>
<td>DR</td>
</tr>
<tr>
<td>BCF</td>
</tr>
<tr>
<td>MF</td>
</tr>
<tr>
<td>PIF</td>
</tr>
</tbody>
</table>

*Source: Eviews 9 output*
Causality between DR, BCF, MF, PIF, and
That there exist relationships between variables does not necessarily imply causality. To test the existence of causality, the study employs the Granger Causality procedure to test the direction of causality among the nominated variables of DR, BCF, MF, and PIF. The results of the pairwise Granger Causality test are summarized on Table 8. It can be seen from the Table that BCF granger-caused PIF (F= 3.26327; prob. = 0.0484), On the other hand, PIF does not granger-cause BCF (F=0.9883; prob. = 0.9061) and BCF granger caused MF (F=3.31143; prob. 0.0464), on the other hand MF does not granger caused BCF (F=2.17275; prob. 0.1268). This implies the existence of are unidirectional causality from BCF to PIF and BCF to MF not vice versa. Thus we reject the null hypothesis of no causal relationship between BCF and PIF as well as BCF and MF

Table 9: Pairwise Granger Causality Tests

<table>
<thead>
<tr>
<th>Null Hypothesis:</th>
<th>Obs</th>
<th>F-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCF does not Granger Cause DR</td>
<td>46</td>
<td>0.10392</td>
<td>0.9015</td>
</tr>
<tr>
<td>DR does not Granger Cause BCF</td>
<td></td>
<td>0.04628</td>
<td>0.9548</td>
</tr>
<tr>
<td>MF does not Granger Cause DR</td>
<td>46</td>
<td>0.05269</td>
<td>0.9487</td>
</tr>
<tr>
<td>DR does not Granger Cause MF</td>
<td></td>
<td>0.06381</td>
<td>0.9383</td>
</tr>
<tr>
<td>PIF does not Granger Cause DR</td>
<td>46</td>
<td>0.25609</td>
<td>0.7753</td>
</tr>
<tr>
<td>DR does not Granger Cause PIF</td>
<td></td>
<td>0.20940</td>
<td>0.8119</td>
</tr>
<tr>
<td>MF does not Granger Cause BCF</td>
<td>46</td>
<td>2.17275</td>
<td>0.1268</td>
</tr>
<tr>
<td>BCF does not Granger Cause MF</td>
<td></td>
<td>3.31143</td>
<td>0.0464</td>
</tr>
<tr>
<td>PIF does not Granger Cause BCF</td>
<td>46</td>
<td>0.09883</td>
<td>0.9061</td>
</tr>
<tr>
<td>BCF does not Granger Cause PIF</td>
<td></td>
<td>3.26327</td>
<td>0.0484</td>
</tr>
<tr>
<td>PIF does not Granger Cause MF</td>
<td>46</td>
<td>1.37128</td>
<td>0.2652</td>
</tr>
<tr>
<td>MF does not Granger Cause PIF</td>
<td></td>
<td>2.53465</td>
<td>0.0916</td>
</tr>
</tbody>
</table>

Source: Eviews 9 output

Vector Error Correction Model
To give room for the short run dynamics in determining the co integration relationship between the dependent and independent variables, we apply the Vector Error Correction Model so as to restrict the long run relationship.

BCF is statistically significant and negatively related to DR in the short run and has an adjustment coefficient of -0.20 percent, which measures the speed of adjustment and explains level variation with the DR. MEF is statistically not significant and negatively related to DR in the short run and has an adjustment coefficient of 4.77 percent, measuring the speed of adjustment and explains level variation with the DR. PIF is statistically not significant and positively related to DR in the short run and has an adjustment coefficient of 0.27 percent, which measures the speed of adjustment and explains level variation with the DR.

CONCLUSION AND RECOMMENDATIONS
Specifically, the dynamic factor model was adopted because it is a statistical technique used to detect common patterns in a set of time series and relationship between these series and explanatory variables. Whereas, in this instance, default rate was modeled against business cycle, macroeconomic, banking
regulation factors. These extracted common factors are then regressed to confirm the existing relationship between them. In the course of the study, we applied the quasi-experimental research design to avoid the challenges of randomization and selection bias. Therefore the application of the dynamic factor analysis will naturally fit the requirement of patterning a qualitative experiment as applicable in quasi-experimental research.

In applying the DFM, we found the following: Factor 1 is identified as Business Cycle Factor with an overall variability of 46.948% and is positively related with the predictive variable, Default Rate, though not significant at 5%. In other words, each of the variables loaded under factor 1 has a positive relationship with the dependent variable, which is simply indicating a direct relationship. Implying that an increase in explanatory variables will lead to increase on predictive and vice versa. Factor 2 is identified as Macroeconomic Factor. Its variability of 17.662% is significant at 5%. It has a positive relationship with the predictive variable. This relationship is not expected but it is in line with economic theory. Scholars are linking loan portfolio credit with macroeconomic factor. Their studies establish that default risk tends to rise during economic downturns. However, banks with higher exposures to macroeconomic risks are expected to have higher non-performing loans, while, Factor 3 is known as Price Indicator Factor. It accounts for 14.379% variability, and has a positive relationship with the predictive variable, default rate, though not Significant at 5% level.

Therefore, we recommended the creation of capital buffers beyond the minimum requirements needed during economic booms in order to tackle procyclical effects prescribed in Basel II as a way to help enshrine financial stability in the banking system; contemporary macroeconomic issues should be incorporated in modeling credit risk to enhance financial stability with the view to cushioning against increase in bankruptcies, volatility of collateral and widening practice of off-balance sheet financing; and lastly, to abate corporate defaults, lending policies of financial in Nigeria institutions should reflect the dynamics of inflation and its associated pressures it cause the Nigerian economy.

REFERENCES


