

# **Analysing Financial System Stability: Research Department**

## **Executive Summary**

The recent 2007-09 global financial crisis and the 2009 Nigerian near-financial crisis have emphasized the need for the analysis and integrated management of global and domestic financial systems. International standard setting institutions, like the Basel Committee for Banking Supervision and the International Monetary Fund (IMF), Central Banks Worldwide as well as the private sector have been working on a series of proposals so as to have a more stable and efficient financial system. The key initiatives pursued in this regard include measuring and managing systemic risk and the development and usage of macro-prudential policies that utilise macro-prudential indicators to ensure stability of financial systems. The overall aim of these two and several other initiatives are the measurement and strengthening of financial system stability.

Analyzing financial system stability is necessary because by identifying individual institutions, particularly Systemically Important Financial Institutions (SIFIs) posing big threats to financial system stability, measures and targets can help in targeting increased supervisory standards. In addition, by indicating that the potential for financial instability is rising (i.e., providing early warning signals), metrics can signal to policymakers a need to tighten the so-called macro-prudential policies.

However, financial system stability is not easy to define and measure due to the interdependence and the complex interactions of different parts of the overall financial system among themselves with the real economy and with cross-border dimensions of elements. The adopted framework to

measure financial stability should incorporate three elements: probabilities of failure in individual financial institutions, loss given default in the financial institutions, and correlation of defaults across the institutions.

Several researchers from standard setting organisations, central banks and academia have attempted to measure systemic risk as a step to measuring financial stability. Bank Negara Malaysia and German Central Bank (Deutsche Bundesbank) have used the Contingent Claims Analysis (CCA) to analyze their financial system stability. The IMF has also used the CCA approach in stress testing exercises of the Financial Sector Assessment Program (FSAP) for Germany, Spain, Sweden, the United Kingdom, and the United States between 2010 and 2012 and the Global Financial Stability.

Analysis of financial stability is usually carried out using macro-prudential indicators, based on FSIs. However, there is increasing use of more sophisticated market-based indicators (such as relative stock market indices, and distance-to-default indicators) and stress testing in addition to using the macroprudential indicators to analyse financial stability.

The CCA approach was used to estimate the implied market value of assets and their volatility for the firms considered (63 in total, with market capitalization representing 10% of the new rebased GDP). This was then used to calculate the Distance-to-Distress/Default (DD), the Probability-of-Default (PD), as well as the expected losses of the firms, sectors and the whole system. Expected loss for the system is the sum of all the implicit put options of each institution.

## Findings

- This paper derives default Probabilities of Default and Distance-to-Default from Merton model and applies this to a number of Nigerian financial and non-financial quoted companies over the period from January 2, 2012 to December 2013. We argue that this model satisfies the macro-prudential approach to financial system stability analysis. On the basis of the Merton model, we constructed a system-wide financial stability measure for Nigeria, which builds on the put options of the banking, insurance, pension sectors, corporate and manufacturing sectors as traded on the floor of the Nigerian Stock Exchange (NSE).
- Distance-to-Distress measure of financial stability (Weighted DD) presents a decrease in financial stability from June 2012 to December 2013, disagreeing with Average Unweighted DD, which can be attributed to Banking, Financial and General Services sectors' instability as depicted by the PD measure. Distance-to-Distress measure of financial system stability could be used for financial system stability analysis by the FSRCC, CBN and other related agencies.
- Our analysis suggests that the Merton model appears to be useful in ranking sectors according to their contribution to financial system stability. The model also provided a means of measuring financial system stability based on individual firms, sectors and the financial system as a whole using several forward-looking measures.
- Our analysis suggests that it is useful to look at the financial system as a portfolio of counterparty exposures, the counterparties being

financial institutions, and then analyze the contribution of each firm to different sectors and the whole system as a portfolio of firms.

- The presented measures for financial stability (broken down in probability and distance to default measures) offer a number of insights which may prove useful for policy purposes. First, they contribute to measuring financial system stability, thus facilitating the identification of risks and providing a guideline for policy efforts. This function has been enhanced since the measures were applied to individual firms and sub-sectors as in this paper. This could help to map vulnerabilities more precisely which could form the basis for pre-emptive or corrective action to improve the stability of the system.
- The analysis also shows that forward-looking risk measures that utilise market data provide useful information for carrying out surveillance and risk assessments of financial system stability and for stress testing. They are a good complement to the main efforts in fundamental analysis of quantitative and qualitative factors. A forward-looking monitoring program to identify sources of systemic risk can help to develop pre-emptive policies to promote financial stability.
- The study indicates the importance of probability-of-default (PD) as a key concept in any analysis of financial fragility and central to the Basel II and III regulatory frameworks, (Goodhart and Tsomocos, 2007). Similarly, financial (in)stability is generated by the probability-of-default (PD) and bankruptcy of firms within the system. A model that captures probability of default of individual firms, that can be aggregated into a system-wide measure should

therefore be used for financial stability analysis since “any serious theory of systemic (in)stability has to focus on PD” (Goodhart and Tsomocos, 2007)

## **Recommendations**

- This analysis was carried out based on only two time periods: June 2012 and December 2013. The FSRCC and NDIC/CBN should carry out this analysis on a quarterly basis so as to *pre-emptively avert, mitigate or manage any potential threat* before it materializes. German central bank (Deutsche Bundesbank ,2005), and Bank Negara Malaysia use this approach as part of their Financial Stability Review. The IMF has also used Contingent Claims Analysis Approach for stress testing exercise of the Financial Sector Assessment Program (FSAP) for Germany, Spain, Sweden, the United Kingdom, and the United States between 2010 and 2012 and the Global Financial Stability (Jobst and Gray, 2013).
- The FSRCC, NDIC, CBN and other stakeholders should initiate or continue enhancing the forward-looking capability of its surveillance framework by having a more robust assessment of risks in the banking, financial services and corporate sectors in an integrated or holistic manner so as to better enhance the stability of the overall financial system. Forward-looking models, like the Distance-to-Default model used in this paper, should be used in conjunction or as complementary tools to standard regulatory measures to enhance financial system stability.

For instance, Bank Negara Malaysia uses the z-score (based on discriminant analysis) and modified distance to default which

*“provide important insights on emerging stress and risks, thereby providing sufficient lead time for the Bank to formulate appropriate policy measures pre-emptively to avert, mitigate or manage such threats. The quantification and measurement of risks enable more robust stress tests to be performed to assess the direct and possible feedback effects from plausible shocks to the system. ...*

*Movements in the median z-score and weighted average modified distance to default are tracked to detect changes in the direction and average level of credit risk both at the macro as well as industry and company specific levels. In addition, Altman z-scores at the 75<sup>th</sup> and 25<sup>th</sup> percentile are also used to monitor the changes in the level of credit risk for firms with higher and lower credit quality, enabling a more complete assessment across different credit qualities.”.Bank Negara, 2008*

Suggested areas requiring further research are as follows:

- Given the varying business characteristics across different firms and sectors, the FSRCC, NDIC and CBN should develop sector specific z-scores based on the financial statements and default experiences of Nigerian businesses. These stakeholders should map the modified distance to default model to historical incidences of bond and loan defaults by Nigerian businesses, thereby enabling estimates of default probability and frequency to be more reflective of the future level of non-performing loans in the corporate sector.
- The FSRCC, CBN and other agencies can also build a model that incorporates forward-looking measures with macro-economic variables for better measurement of financial system stability. The time pattern of asset returns of each financial institution (or of the

risk indicators) can be used as the dependent variable in a factor model. Key factors driving these asset returns could include GDP, domestic and foreign interest rates, exchange rate, domestic and foreign equity indices, etc. A separate macroeconomic scenario generating model, e.g. a macroeconomic vector autoregressive model, could then be used to test the impact of scenarios on the key factors, which feed into the financial institution's assets. This, in turn affects the credit risk indicators and the value of equity capital.

- The NDIC carried out a previous study on measuring systemic risk based on the widely acclaimed SRISK approach pioneered by professors from Stern Business School. Given the complexity of the financial system and its multidimensional nature, the recommendation of using several models simultaneously to measure financial system stability should be considered. The implemented SRISK approach and the DD measures adopted in this paper should be used in tandem for enhancing financial system stability.

## **Introduction**

The recent 2007-09 global financial crisis and the 2009 Nigerian near-systemic financial crisis has emphasized the need for the analysis and integrated management of global and domestic financial systems. International standard setting institutions like the Basel Committee for Banking Supervision and the International Monetary Fund (IMF) central banks worldwide as well as the private sector have been working on a series of proposals and initiatives with the aim of building be more stable and efficient financial systems. The key initiatives pursued in this regard

include measuring and managing systemic risk and the development and usage of macroprudential policies that utilise macroprudential indicators (MPIs) to ensure stability of financial systems. The overall aim of these two and several other initiatives are the measurement and strengthening of financial system stability.

Systemic risk is very important due to its link with financial stability. It is necessary to measure, and manage occurrence of events that could lead to systemic risk in order to ensure financial stability. In addition, a key lesson drawn from the global crisis is the limitation of the traditional micro-prudential regulations to identifying weaknesses of the financial system as a whole, such as the build-up of systemic risk. This has resulted in a shift towards macro-prudential approach in financial stability analysis. In contrast to the micro-prudential analysis, the macro-prudential analysis emphasises a holistic approach to monitoring stability of financial systems by observing macroeconomic and market-based data, qualitative and structural information, and the MPIs and financial soundness indicators (FSIs).

Alexander (2010) provides four distinct policy applications of systemic risk and financial stability measures, as follows:

- (a) by identifying individual institutions, particularly, systemically important financial institutions (SIFIs) posing big threats to financial stability, measures and targets can help in targeting increased supervisory standards;
- (b) by identifying specific structural aspects of the financial system that are particularly vulnerable, measures and targets can help policymakers identify where regulations need to be changed;

- (c) by identifying potential shocks to the financial system posing big threats to stability metrics may help guide policy to address those threats; and
- (d) by indicating that the potential for financial instability is rising (i.e., providing early warning signals), metrics can signal to policymakers a need to tighten so-called macroprudential policies.

There is no widely accepted definition of 'financial stability' unlike price stability (Gadanecz and Jayaram, 2009) and therefore, equally, no consensus on what policies should be pursued in the interests of financial system stability (Allen and Wood, 2006). Financial stability is not easy to define and measure due to the interdependence and the complex interactions of different parts of the overall financial system among themselves with the real economy and with cross-border dimensions of elements (Gadanecz and Jayaram, 2009). In the words of the Swedish central bank Governor, 'the concept of stability is slightly vague and difficult to define'. However, it is well understood that "that financial stability is about the absence of system-wide episodes in which the financial system fails to function (crises), and about resilience of financial systems to stress" (Čihák, 2007).

Several researchers from standard setting organisations, central banks and academia have attempted to measure systemic risk as a step to measuring financial stability, develop MPIs and FSIs to capture conditions of financial stability as well as measure the stress or stability of the financial system through several models using the MPIs and other indicators (Evans et al (2000) and Van den End & Tabbae (2005)). As recognised by (Nelson and Perli (2005), Van den End (2006)), in addition to balance-sheet based information, there is need for market

information so as to capture the interactions between bank- and non-bank financial intermediation. In this study we employ contingent claims analysis (CCA) that utilises market information to study measure or assess financial systemic stability. CCA is a proven approach to analyzing and managing risk, including sovereign and financial system stability. The idea of using market data (equity prices) for assessment of financial institutions' soundness comes from the insight that corporate securities are contingent claims on the asset value of the issuing firm.

The CCA is a generalization of the option pricing theory pioneered by Black–Scholes (1973) and Merton (1973). Option pricing methodology has been applied to a wide variety of contingent claims. When applied to the analysis and measurement of credit risk, CCA is commonly called the "Merton Model." It is based on three principles: (i) the values of liabilities are derived from assets; (ii) assets follow a stochastic process; and, (iii) liabilities have different priority (i.e., senior and junior claims).

The basic analytical tool in this framework is the risk-adjusted balance sheet, which shows the sensitivity of the country's assets and liabilities to external "shocks" (Gray et al, 2007). At the national level, the sectors of the country economy are then viewed as interconnected portfolios of assets, liabilities, and guarantees. The Merton model used in this study is a multi -sector model that integrates the default risks of various sectors into a systemic model. This approach has been found to be reliable in predicting default and fits in the macro-prudential approach (Borio, 2003 and Gray & Malone (2008)) and makes it useful for measuring financial stability (Gray et al (2007), Gray & Malone (2008) and Van den End & Tabbae (2005)).

The adopted framework incorporates the three elements, argued by Cihak (2007), that a good measure of systemic stability needs to possess, namely: probabilities of failure in individual financial institutions, loss given default in the financial institutions, and correlation of defaults across the institutions. According to Gray et al (2007), the "CCA framework provides a forward-looking market-based set of indicators to measure the vulnerability of various sectors of the economy and is well-suited to capturing nonlinearities and to quantifying the effects of asset-liability mismatches within and across institutions".

The contribution of this paper is in using probability of default, distance to default and market data coupled with balance sheet liabilities data based on individual institutions' forecasted failures or stability metric, as key measures of stability.

Financial stability analysis, macroprudential supervision and measuring system risk are set out in section 2. The section also discusses macroprudential indicators and the various ways of studying financial stability. Section 3 deals with the details of Contingent Claims Analysis, including option pricing theory to study financial system stability. The section explains the Merton model with a description of the way in which it can be applied to the various sectors of the economy and the financial system so as to measure financial system stability. Subsequently, section 4 presents the data used in the analysis and applies the CCA approach to analyse financial stability in Nigeria, with an evaluation of the measure's reliability and a discussion of the possibilities for stress testing. The paper concludes with some policy -relevant observations. Finally, in Section 5, we summarize our findings and propose possible lines of further research in order to measure financial system stability in Nigeria.

### **3.0 Financial Stability Analysis, Macroprudential Supervision and Measuring System Risk**

#### **2.1 What is financial stability?**

Unlike price stability, financial stability has neither an established definition (Čihák, 2006), (Gadanecz and Jayaram, 2009) nor an aggregate indicator that the central bank can use as a measure of financial instability (Čihák, 2006). There is no consensus on the basic theoretical financial stability framework and no such framework that relates to systemic stability (Goodhart and Tsomocos, 2007). The lack of consensus on the definition of financial system stability could be due to the fact that financial stability is a multi -faceted concept, making it hard to measure (Van den End & Tabbæ, 2005).

The financial system is regarded as stable in the absence of excessive volatility, stress or crisis (Gadanecz and Jayaram, 2009). The European Central Bank defined financial stability as "a condition in which the financial system – comprising financial intermediaries, markets and market infrastructure – is capable of withstanding shocks and the unravelling of financial imbalances, thereby mitigating the likelihood of disruptions in the financial intermediation process which are severe enough to significantly impair the allocation of savings to profitable investment opportunities" (ECB, 2007).

Monitoring financial stability therefore requires an explicit understanding of both how traditional and evolving financial markets relate to each other and how they relate to economic conditions (Brave and Butters, 2011).

According to Van den End & Tabbæ (2005), financial stability relates to the functioning of financial markets, institutions and infrastructure and to the interaction between the financial sector and the real economy. This

complexity implies that financial stability cannot easily be summarised in a single measure, like the inflation index for price stability.

The complexity and vagueness of the definition of financial system stability has led many analysts and researchers to focus on the risks and vulnerabilities of the financial system due to their ease of modelling. The problem with this approach is that viewing financial stability from crisis angle is too narrow given that different countries have experienced different types of crises ranging from banking crisis, currency crisis to debt crisis or even stock market crises. Each crisis can also be defined in several ways and is based on different quantifiable variables, Gadanecz and Jayaram (2009).

## **2.2 What is Systemic Risk**

The task of measuring systemic risk is difficult because there is no agreed definition of such an important risk. This is because it is difficult to manage what cannot be measured and before we can measure systemic risk, we need to define or characterize it. Policymakers, regulators, academics and practitioners have given different definitions to systemic risk.

Systemic risk has been defined as the probability that a series of correlated defaults among financial institutions, occurring over a short time span, will trigger a withdrawal of liquidity and widespread loss of confidence in the financial system as a whole (Billio et al, 2010). The European Central Bank (ECB, 2010) views systemic risk as a risk of financial instability so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially. Acharya et al, 2010 define this risk in terms of correlated exposures, Mishkin (2007) focussed on information disruptions, Moussa

(2011) defined this risk with respect to contagion and in terms of negative externalities by (Financial Stability Board, 2009). Systemic risk occurs if and only if there is an aggregate shortage of capital in the financial sector such that a reduction in lending by the failure of one bank cannot be offset by other financial institutions (Acharya and Steffen, 2012).

A dominant definition is that systemic risk has to do with “the risk of experiencing an event that will affect the well-functioning of the entire financial system” (Marquez et al, 2009). Bank for International Settlements in its annual report of 1993-1994 defined systemic risk as “the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default, with the chain reaction leading to broader financial difficulties”. However, systemic risk can simply be defined as any broad-based breakdown in the financial system

It can be inferred that systemic risk has two components; namely: An event that causes the failure or dysfunctionality of a critical number of market participants, and a contagion mechanism which propagates the failure and/or dysfunctionality to a broader number of participants or the entire system (Marquez et al, 2009). The objective of financial stability is to limit the build-up of systemic risk.

There are several techniques proposed in the literature for measuring systemic risk, financial stability analysis and the systemic importance of institutions (Bisias et al., 2012) mainly developed both before and during the 2007-09 financial crisis. A widely used technique for measuring systemic risk and assessing financial system stability is based on Merton (1974) structural model or contingent claims analysis.

To measure systemic risk, the portfolio is basically all the firms that make up the financial system. In this context, a number of assumptions regarding the likelihood of default (PDs) and the severity of losses (LGDs) and an assumed dependence structure, an aggregate loss distribution, which represents the total losses of all the institutions in the financial system, can be derived from the losses of the individual institutions. Others, like Huang, Zhou and Zhu (2009) use the contingent claim analysis framework as a first step in determining the systemic importance of financial institutions. In particular, in a second step they use specific allocation procedures to allocate the total level of systemic risk to individual institutions.

The IMF has used Contingent Claims Analysis Approach the stress testing exercise of the Financial Sector Assessment Program (FSAP) for Germany, Spain, Sweden, the United Kingdom, and the United States between 2010 and 2012 and the Global Financial Stability (Jobst and Gray, 2013).

Van den End and Tabbae (2005), construct a system -wide financial stability measure for the Netherlands that builds on the put options of the banking, insurance and pension sectors. This measure approximates the probability and the potential loss of stress in the financial system. The authors argue that this method satisfies the macro-prudential approach. Van den End and Tabbae tested the measure against various indicators of default risk, and concluded that it is a reliable proxy.

Gray and Jobst (2010) propose using contingent claims analysis (CCA) to measure systemic risk from market-implied expected losses, with immediate practical applications to the analysis of implicit government contingent liabilities, i.e., guarantees. In addition, the framework also helps quantify the individual contributions of financial institutions to

overall contingent liabilities in the event of a systemic distress. Gray and Jobst (2010) use CDS spreads in a contingent claims analysis of financial firm risk. Adrian and Brunnermeier's (2010) conditional value at risk (CoVaR) and the International Monetary Fund's (2009b) related "Co-Risk" models of shared exposures similarly rely on firm-level market prices.

The "Co-Risk" measure, first proposed in the IMF's 2009 Global Financial Stability Review (International Monetary Fund, 2009a), examines the co-dependence between the CDS of various financial institutions. It is more informative than unconditional risk measures because it provides a market assessment of the proportional increase in a firm's credit risk induced, directly and indirectly, from its links to another firm. The distressed insurance premium (DIP) of Huang, Zhou, and Zhu (2009b) measures the conditional expected shortfall (CoES) of an institution, conditional on systemic distress. The DIP represents a hypothetical insurance premium against systemic distress, defined as total losses exceeding a threshold level of 15% of total bank liabilities.

Using stock-market information, Lehar (2005) monitors the risk in a bank regulator's portfolio by estimating the probability of a simultaneous default of several banks using the Merton (1974) model.

### **2.3 Macprudential Indicators and Policy**

Macro-prudential analysis relies on micro indicators (that is indicators of risks of individual institutions), which are then aggregated and used for macroprudential analysis (Van den End & Tabbae, 2005). The IMF's Financial Soundness Indicators (FSIs), which contain a basic set of such macro-prudential indicators<sup>2</sup>, as well as aggregated micro data, macro -

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<sup>2</sup> The macroprudential indicators (MPIs) are developed as indicators of the health and stability of financial systems and conceived to be critical in producing reliable assessments of the strengths and vulnerabilities of financial systems and to enhancing disclosure of key financial information to markets.

economic variables (such as interest rates, GDP growth and credit expansion) are also used as financial stability indicators.

There are a total of 39 FSIs divided into two groups. The first group consists of the main indicators (the core set) relating to the banking sector (12 indicators). The remaining 27 recommended indicators belong to the second group (the encouraged set), which includes some other banking sector indicators, but also indicators from non-bank financial institutions, non-financial corporations, households, financial markets and property markets. The inclusion of non-banking sector indicators in the FSIs reflects the interconnection of the financial and real sectors, for example, unfavourable developments in the corporate sector pass through to the loan portfolio of banks and may thus have a negative effect on financial stability.

According to Geršl and Heřmánek (2006), the objective of the set of financial stability indicators is to provide users with a rough idea of the soundness of the financial sector as a whole. On the other hand, the objective of macro-prudential policy is to focus on how financial institutions, markets, infrastructure and the wider economy interact with each other. The development of macroprudential policy instruments involves adapting existing microprudential tools, such as the individual FSIs, and limits on activities that increase systemic vulnerabilities and risks.

The Committee on the Global Financial System of the Bank of International Settlements (CGFS, 2010) discussed the issues involved in operating macroprudential instruments. According to CGFS, assessing the transmission of macroprudential interventions using MPIS in the financial system is very difficult because we have not fully understood how the financial system behaves and interacts with the macroeconomy. The first reason for the lack of the understanding is the plenitude of instruments

(like lending restrictions) that are helpful as policy measures which could potentially be tailored to conditions in particular sectors. It should be noted however that measures targeting specific markets might increase imbalances in other areas. Second, the transmission mechanism is likely to change over time with changes in financial intermediation practices and the structure of the financial system. Innovations in Financial products, consolidation and can change risk distributions in unpredictable ways.

Signal extraction to understand build-up of financial risks using macroprudential policy framework is also difficult (CGFS, 2010). There is a need to accurately assess financial imbalances and vulnerabilities at both the aggregate and disaggregated levels, which may be more apparent at the sectoral level, given that imbalances and exposures do not typically develop evenly across the financial system or sectors of the real economy. "The difficulty of aggregating sector-specific measures into credible evidence of an overall macroprudential problem might lead policymakers to take action mainly at a disaggregated level, even though the actions might be motivated primarily by macroprudential concerns. The danger here is that the intent of macroprudential policy might not be clear" (CGFS, 2010).

Another signal extraction issue is that that policy measures will not be applied uniformly and proportionately across sectors. After all, macroprudential indicators, though useful, are mostly sector-specific, and therefore do not quantify the multifaceted nature of financial stability (Van den End and Tabbæ, 2005).

## **2.4 Quantifying financial stability**

Definition of financial stability is only useful for crisis prevention and management as well as policy analysis when it is operational and quantifiable. The analysis of financial stability is generally based on several risk factors therefore a single model may not satisfactorily capture all the risk factors. Rather, a number of models is needed (Bårdsen et al, 2006).

Bårdsen et al (2006) outline the minimum structural characteristics that models quantifying financial stability should ideally be able to include as follows: the possibility of contagious failures between banks and their borrowers; as an important element in contagion. It is essential that a model exploring contagion should include a default parameter; since another important aspect of the real world is that markets are incomplete and not every eventuality can be hedged, it is also essential for a model exploring systemic risk to include liquidity risk and/or the incompleteness of financial markets and include genuine macroeconomic conditions. Other characteristics are structural micro-foundations due to regime changes and discontinuous changes of economic and financial variables; be empirically tractable with analytically coherent framework that may be more relevant for financial stability analysis; be useful for forecasting and policy analysis and can be tested.

The indicator needed to quantify financial stability must be made up of different components of the financial system, as "financial stability can be seen as being consistent with various combinations of the conditions of its constituent parts..." (Van den End and Tabbæ, 2005). According to Cihak (2007), a good measure of financial systemic stability should incorporate three elements of: probabilities of failure in individual financial institutions, loss given default in the financial institutions, and correlation of defaults across the institutions.

The construction of an aggregate financial stability indicator is still in the research and experimental phase (Geršl and Heřmánek, 2006).

The complexity and vagueness of financial stability implies that it can be represented by several indicators that include accounting ratios (e.g., capital to assets), MPIs/FSIs, measures of PoD derived from market prices and option pricing theory, supervisory early warning systems, and others obtained from stress testing. Generally, most balance sheet indicators (nonperforming loans for example) are typically backward-looking indicators of financial distress while market information and ratings of individual institutions are in principle forward-looking (CGFS, 2010).

Analysis of financial stability is usually carried out using macroprudential indicators, based on FSIs. However, there is increasing use of more sophisticated market-based indicators (such as credit-default swaps, relative stock market indices, and distance-to default indicators) and stresstesting in addition to using the MPIs/FSIs to analyse financial stability (Čihák, 2007).

Probability of default (PoD) is a key concept in any analysis of financial fragility and central to the Basel II and III regulatory frameworks (Goodhart and Tsomocos, 2007). Similarly, financial (in) stability is generated by the PoD and bankruptcy of firms within the system. A model that captures PoD of individual firms, that can be aggregated into a system-wide measure should therefore be used for financial stability analysis since “any serious theory of systemic (in) stability has to focus on PoD” (Goodhart and Tsomocos, 2007).

The argument of Goodhart and Tsomocos (2007), further implies that financial instability is characterized by both high probabilities of default and low profits, at both the individual and aggregate levels.

Furthermore, (Brave and Butters, 2011) argues that a way to judge the

validity of measures of financial stability is to follow the narrative approach and link their values to significant events in a nation's financial history

Given the above desired characteristics of models and indicators of financial stability, we therefore focus the attention of this paper to market data and models that explicitly measure probability of default or the default likelihood for each institution.

### **3.0 Contingent Claims Analysis**

A contingent claim is any financial asset whose future payoff depends on the value of another asset. CCA is used to construct risk-adjusted balance sheets, based on three principles: (i) the values of liabilities (equity and debt) are derived from assets; (ii) liabilities have different priority (i.e., senior and junior claims); and (iii) assets follow a stochastic process. The liabilities consist of senior claims (such as senior debt), subordinated claims (such as subordinated debt) and the junior claims (equity or the most junior claim). Balance sheet risk is the key to understanding credit risk and crisis probabilities. Default happens when assets cannot service debt payments. Uncertain changes in future asset value, relative to promised payments on debt, is the driver of default risk. As total assets decline, the value of risky debt declines and credit spreads on risky debt rise. The asset price of a firm (such as the present value of income flows and proceeds from asset sales) changes over time and may be above or below promised payments on debt which constitute a default barrier. Uncertain changes in future asset value, relative to the default barrier, determine the probability of default risk, where default occurs when assets decline below the barrier. When there is a chance of default, the repayment of debt is considered "risky," unless it is guaranteed in the event of default. Contingent claims analysis is a generalization of the

option pricing theory pioneered by Black-Scholes (1973) and Merton (1974).

In the model of Merton (1974), the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. As inputs, Merton's model requires the current value of the company's assets, the volatility of the company's assets, the outstanding debt, and the debt maturity. To calculate the probability of default, the model subtracts the face value of the firm's debt from an estimate of the market value and then divides this difference by an estimate of the volatility of the firms' assets. The outcome is known as the distance to default, which is then substituted into a cumulative density function to calculate the probability that the value of the assets will be less than the value of debt at the forecasting horizon.

The Merton DD model makes two important assumptions; the first is that the value of a firm follows geometric Brownian motion,

$$dV = \mu V dt + \sigma_V V dW \quad \text{eqtn. (1)}$$

Where  $V$  is the total value of the firm,  $\mu$  is the continuously compounded return on  $V$ ,  $\sigma_V$  is the volatility of the firms' assets and  $dW$  is a standard Wiener process. The second assumption of the Merton DD model is that the firm has issued only one zero-coupon bond maturing in time  $T$ . In the model, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the value of the firm's debt and a maturity of time  $T$ . The value of this call option can be described by the Black-Scholes-Merton formula. By put-call parity, the value of the debt is equal to the value of a risk-free discount bond minus the value of a put option. The Merton model specifies that the equity value of a company satisfies

$$E = VN(d_1) - e^{-rt} FN(d_2) \quad \text{eqtn. (2)}$$

In which  $E$  is the market value of the firm's equity,  $F$  is the face value of the debt,  $r$  is the risk-free rate,  $N(\cdot)$  is the cumulative standard normal distribution function and  $d_1$  and  $d_2$  are given by

$$d_1 = \frac{\ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \quad \text{eqtn. (3)}$$

and

$$d_2 = d_1 - \sigma_V \sqrt{T} \quad \text{eqtn. (4)}$$

The Merton DD model is based upon two important equations. Equation (2) expresses the equity value as a function of the total value. Equation (3) relates the volatility of the firm's asset value to the volatility of its equity. The value of equity is a function of the value of the firm and time, so that it follows from Ito's Lemma that

$$\sigma_E = \left( \frac{V}{E} \right) \frac{\partial E}{\partial V} \sigma_V \quad \text{eqtn. (5)}$$

In the Black-Scholes-Merton model, it can be shown that  $\partial E / \partial V = N(d_1)$ , so that the volatilities of the firm's assets and its equity are related by

$$\sigma_E = \left( \frac{V}{E} \right) N(d_1) \sigma_V \quad \text{eqtn. (6)}$$

In the Merton DD model the value of the option is observed as the total value of the firm's equity, while the underlying value of the asset is not directly observable. The equity value  $E$  can be observed from the market by multiplying the outstanding shares by the current stock price. The volatility of the equity  $\sigma_E$  can be estimated by using historical stock return data. It is typical to use a forecasting horizon of one year ( $T = 1$ ), and as such a 12-months risk-free rate can be applied. For the face value of debt  $F$ , we can use the book value of the total liabilities. All variables are thus

observable except for the value of the assets  $V$ , and its volatility  $\sigma_V$ . These values have to be inferred from equations (2) and (5). First an initial value of  $\sigma_V$  is estimated by

$$\sigma_V = \sigma_E \left( \frac{E}{E + F} \right) \quad \text{eqtn. (7)}$$

The value of the assets  $V$  can then be calculating by using equation (2) and the calculated  $\sigma_V$  from equation (7). This will be done on a daily basis of the previous year. With these values of  $V$ , we will calculate the implied log return on assets each day, and use this return series to generate new estimates of  $\sigma_V$  and  $\mu$ . Once this numerical solution is obtained, the distance to default can be calculated by

$$DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \quad \text{eqtn. (8)}$$

The corresponding probability of default is

$$PoD = N(-DD) \quad \text{eqtn. (9)}$$

The basic analytical tool in the CCA is the risk-adjusted balance sheet, which shows the sensitivity of the enterprise's assets and liabilities to external "shocks."

At the national level, the sectors of an economy are viewed as interconnected portfolios of assets, liabilities, and guarantees—some explicit and others implicit. Traditional approaches have difficulty analyzing how risks can accumulate gradually and then suddenly erupt into a full-blown crisis. The CCA approach is well-suited to capturing such "non-linearities" and to quantifying the effects of asset-liability mismatches within and across institutions. Risk adjusted CCA balance

sheets facilitate simulations and stress testing to evaluate the potential impact of policies to manage systemic risk.

The same general principles of contingent claims that apply to analysis of a single firm can also be applied to an aggregation of firms. The liabilities of a firm, a portfolio of firms in a sector, or the financial sector can be valued as contingent claims on the assets of the respective firm or sector.

### **Financial Stability Risk Measures based on CCA**

The Merton model solves for risk-neutral probabilities of default that represent the probability that the asset value of a firm will fall below the value of debt, assuming that the underlying asset return (change in asset value) process has a mean return equal to the risk-free rate. This model views a firm's liabilities (equity and debt) as contingent claims issued against the firm's underlying assets. By backing out asset values and volatilities from quoted stock prices and balance sheet information, the Merton model produces instantaneous updates of a firm's default probability. The default probability in the model is a nonlinear function (where the default probability has to be solved for iteratively) of the firm's stock price, stock price volatility, and leverage ratio.

The famous rating agency, Moody's, has developed a procedure for estimating the default probability of a firm that is based conceptually on Merton's 1974 option-theoretic, zero-coupon, corporate bond valuation approach.

Chan-Lau (2006) and Gropp, Vesala and Vulpes (2002) showed equity prices are used in the famous Merton model (Merton, 1974) and its several variants is very useful not only for predicting distress but also for systemic risk analysis and stress testing financial systems. Chan-Lau,

Jobert, and Kong (2004) estimated bank distress using Merton (1974) model for 38 banks in 14 emerging market countries. Their results showed that Merton (1974) model can predict a bank's credit deterioration up to nine months in advance.

Bank Negara (2008) use forward-looking models (z-score and modified distance to default) to provide important insights on emerging stress and risks of the corporate sector. Saldias (2012a and 2012b) compute aggregated and forward-looking distance-to-default called aggregated distance to default (ADD) and portfolio distance to default (PDD) to measure systemic risk in the European banking system.

Market indicators have also been playing a more important role in assessing the efficiency and stability of public sector credit institutions at German central bank (Deutsche Bundesbank, 2005). The distance to default indicator derived by using theoretical option-price-based measures is used by the Bank to measure the improvement in the efficiency and resilience of the German listed firms in both banking and insurance sectors.

Firms or sectors with shorter distances to default are assessed to be associated with higher credit risk and hence a greater probability of default.

For example, European Central Bank (2005) treats the DD as an important forward-looking indicator that can provide early signs of financial fragility.

The distance to default measures the number of standard deviations the expected asset value is away from the default. Thus, a high distance to

default is associated with a low default probability. The DD is defined by the number of the standard deviation of the market value of assets away from the default point. The larger the DD, the greater is the distance of a company from the default point, and the lower is the probability of default. For example, a DD of 2.0 means that default within a year is a two-standard deviation event, presuming the fluctuation of the market value of assets follows the recent historical value, using the current market value of assets as a starting point. Even if the DD becomes zero, it does not mean that the bank fails at that point of time. If short-term debts (liabilities with maturity less than a year) are not rolled over, then the bank would need to exhaust assets in order to repay within a year. The DD being 0.0 or even negative means that the bank will be highly likely to fail unless the asset value improves.

As for the models used to calibrate the DD series, at each point in time  $t$ , the Average Distance-to Default (ADD) is obtained by taking the simple average across the  $N$  individual bank DD series. The definition of the inputs in the PDDs case is the same as in DD and ADD. However, the PDD assumes that individual banks are regarded as a big bank and the balance sheet data of the PDD banks are aggregated into a single series. Hence, the individual annual and interim data on total assets, short-term liabilities and equity are added up across the actual constituents from the portfolio to compute quarterly portfolio's distress barrier before daily interpolation.

In this paper, financial system is viewed as a set of interrelated balance sheets with five sectors – banks, financial services, corporate (manufacturing), corporate (oil and gas) and general services. The liabilities of a firm, a portfolio of firms in a sector, can be valued as contingent claims on the assets of the respective firm or sector. The principles of contingent claims are applied to each firm and then

aggregated to obtain a systemic risk measure based on the recommendation of Gray and Malone (2008) by weighting the individual default probabilities and distance to distress by the estimated market value of assets of each institution to get a system risk indicator. The authors also suggested using the median PoD for the subsector or group and then summing the implicit put options of a portfolio of institutions to get the system expected loss for a given horizon period.

In this section, we applied Merton 1974 model to the firms and sectors. We derive the probability of default and distance to default (DD) based on Merton (1974) model. The probability of default (PoD) and DD in this case are a function of the bank's capital structure, the volatility of the asset returns and the current asset value. The PoD is bank specific and can be mapped into any rating system to derive the equivalent rating of the obligor (Crouhy et. al., 2000).

CCA was used to estimate the implied market value of assets and their volatility for the banks. The market value of equity (i.e. total market capitalization from stock price data) and its volatility was used together with the distress barrier to calculate implied assets and their volatility for each firm in the sectors identified. This was then used to calculate the distance to distress, PDDs, ADDs, the probability of default, as well as the expected losses of the firms, sectors and the whole system. Expected loss for the system is the sum of all the implicit put options of each institution. While some studies (Gray, Merton and Bodie, 2008) aggregate all equity prices and market capitalization as one large firm and the financial sector as one large institution and derive risk measures in this way, one can look at each firm and financial institutions separately and group the firms into sub-sectors. The individual firms can then be aggregated into Average or Weighted PDs or DDs as appropriate. This enables the analyst to identify

the firm or sector that is contributing to the most to financial system instability or has the potential to do same. Remedial or pre-emptive action can then quickly be taken before it becomes a serious issue.

This paper measures financial system stability by analysing systemic risk, based on PDs, DDs and ADDs, for individual firms, sectors and the whole system.

#### **4.0 The Data and Empirical Analysis**

It is well-known that stock market prices reflect the full range of available market information (about credit, currency, interest rate, liquidity and operational risks, etc.). Due to the fact that the financial stability measures are determined based on market prices (equity market capitalisation, volatility of stock prices and interest rates), they also reflect other stability risks in addition to default risk.

Burton and Seale (2005) presented several examples where Moody's KMV distress prediction model, which is based on Merton's 1974 model, could have been used by FDIC to identify when default expectations for an insured institution began to deviate from those for peer institutions. In the presented example, the market provided an unambiguous and quantifiable signal of financial weaknesses that led to the institution's failure some 21 months later.

Our sample is the set of all firms that are listed on the Nigerian Stock Exchange. We include all firms with complete market capitalization and stock price series as well as liabilities information from 2<sup>nd</sup> January 2012 to the end of 2013. The data set includes data (stock returns and market capitalizations, from Datastream) and quarterly data of liabilities.

In our sample, there are 16 banks and 11 financial-services firms (including insurance companies, pension funds and investment management firms). Other firms include 15 oil and gas firms as well as 16 manufacturing firms. The sectors considered in our system-wide financial stability is therefore in line with Van den End and Tabbæ (2005), that constructed a system -wide financial stability measure for the Netherlands based on put options of the banking, insurance and pension sectors. The market capitalization of all the firms used is shown in Table 1.

Table 1: Market capitalization of all the firms used in the analysis

<b>S/No</b>	<b>Sector</b>	<b>No of Firms Used</b>	<b>Total Market Cap (N Millions)</b>	
1	Banks	16	2,917,600.00	35.21%
2	Oil and Gas	15	150,360.00	1.81%
3	Manufacturing	16	5,152,900.00	62.18%
4	Financial Services	8	35,784.00	0.43%
5	General Services	8	30,051.00	0.36%
			<b>8,286,695.00</b>	

The manufacturing sector carries over 62% of the market capitalization of all the firms considered. This is principally due to the influence of Dangote Cement. Banking carries over 35% of the whole market capitalization considered. The cumulative market capitalization for the 63 institutions is 8.286 trillion Naira. For the banking sector, the firms listed

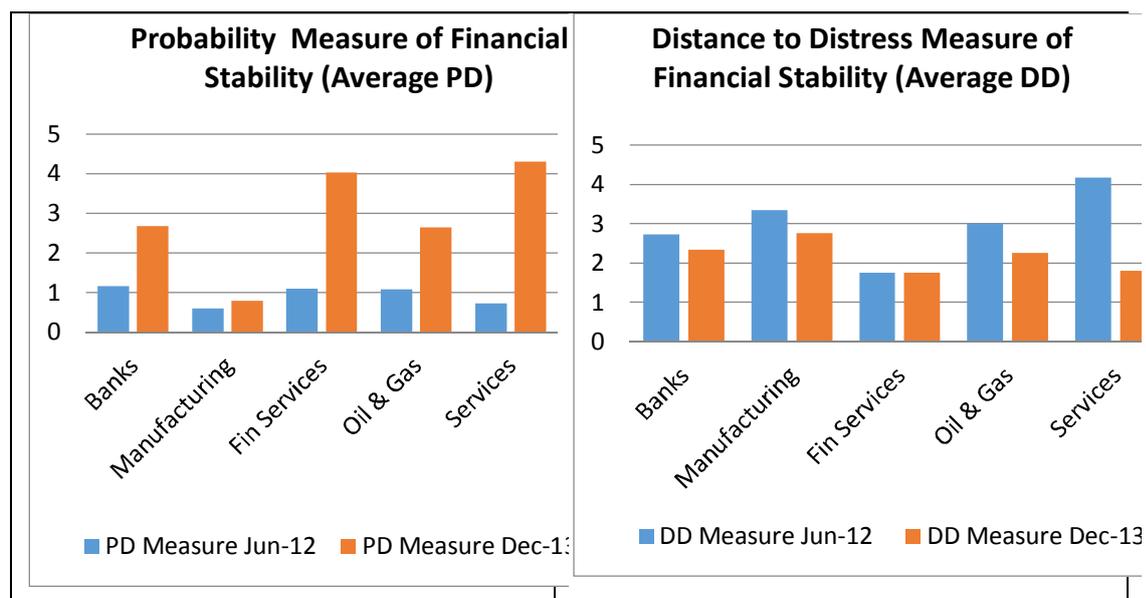
on the NSE and used in this analysis have assets worth more than 90% of the total banking industry assets.

Nigeria’s GDP in 2013 had been revised from 42.4 trillion naira to 80.2 trillion naira (\$510 billion). Therefore, the total market capitalisation of the firms used for the analysis is about 10% of the rebased GDP.

## Results

In this section, we applied Merton 1974 model to the firms and sectors. We derive the probability of default and distance to default (DD) based on Merton (1974) model. The probability of default (PoD) and DD in this case are a function of the bank’s capital structure, the volatility of the asset returns and the current asset value. The PoD is bank specific and can be mapped into any rating system to derive the equivalent rating of the obligor (Crouhy et. al., 2000). This paper measures financial system stability by analysing systemic risk, based on PoDs, DDs and Average DDs (ADDs), for individual firms, sectors and the whole system.

Chart 1: Probability of Default Financial System Stability Measure



The chart above shows both Average probability of default (PD) and Average distance to default (DD) measures for the Nigerian banking, manufacturing, financial services, oil and gas and general services sectors. Based on the unweighted average, the PD measure suggests that financial stability has decreased since June 2012 as at December 2013 for all the sectors. The General Services sector has presented the greatest increment of financial instability from June 2012 to December 2013, followed closely by Financial Services sector. Both Banking as well as Oil and Gas sectors presented very similar increases and are the second most stable sectors of the economy. This measure presented the Manufacturing and General Services as the sectors that contribute the most and the least to financial system stability, respectively. We expected default risk to be typically higher for banks than for other sectors (higher PDs or lower DDs), given the higher leverage in the banks' balance sheets (owing to their funding with borrowed funds, such as deposits and interbank loans, which have relatively short maturities). The Banking sector risk profile has not projected this profile. A clear explanation for this has to be established which may be connected to the risk profiles of the other sectors of the banks. The Appendix shows the individual estimated risk measures for all the firms that form a sector. Analyzing the biggest contributors or firms with the biggest change can add further insight or help in addressing the financial instability.

The unweighted average DD, also reported a decrease in financial system stability from June 2012 to December 2013. As in unweighted average PD measure, the analysis presented Manufacturing and General Services as the sectors that contribute the most and the least to financial system stability, respectively. Oil & Gas and Banking sectors presented very

similar increase and are the second and third most stable sectors of the economy, respectively.

It should be noted from the graphs that the unweighted average PD measure has recorded more dramatic increase in instability than the unweighted average DD measure. It should also be noted that the higher the PD, the more the instability of the sector or firm. However, the higher the DD, the higher the stability of the sector or firm.

Chart 2: Distance to Default Financial System Stability Measure

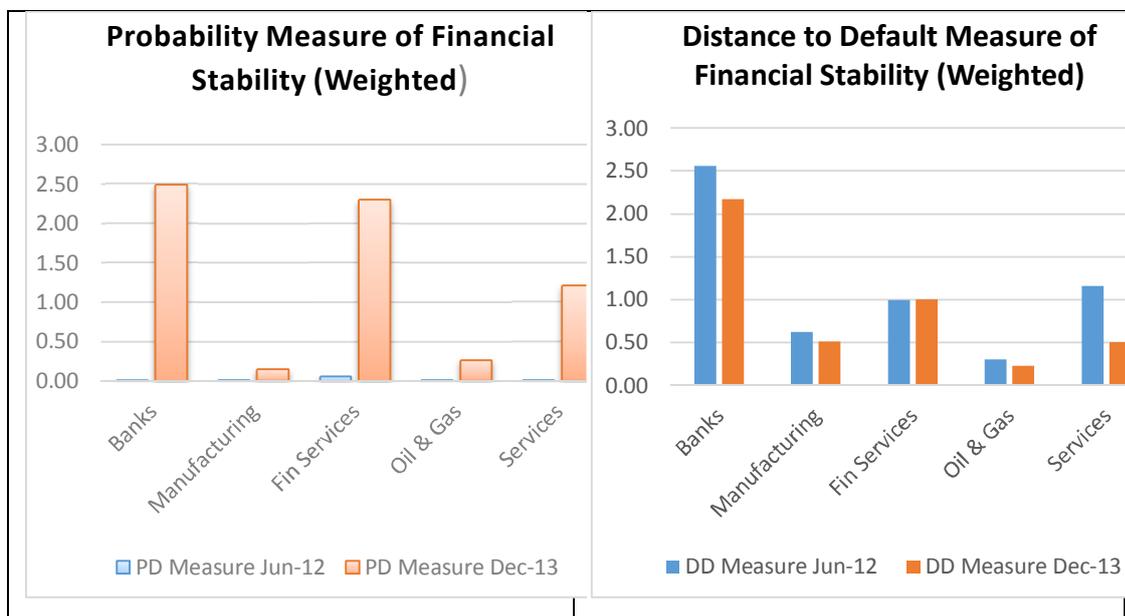


Chart 2 above, the weighted PD and DD measures, also reported a decrease in financial system stability from June 2012 to December 2013. However, the weighted PD measure reported the sectors that contributed the most to financial instability, in decreasing order, as Banking, Financial Services, General Services, then Oil and Gas and finally Manufacturing sector. The weighted DD measure also reported decrease in financial system stability, except in Financial Services that remained the same. The Banking sector contributed the most to financial system stability, followed by Financial Services and then followed by General Services.

Chart 3: Aggregated Financial System Stability Measures

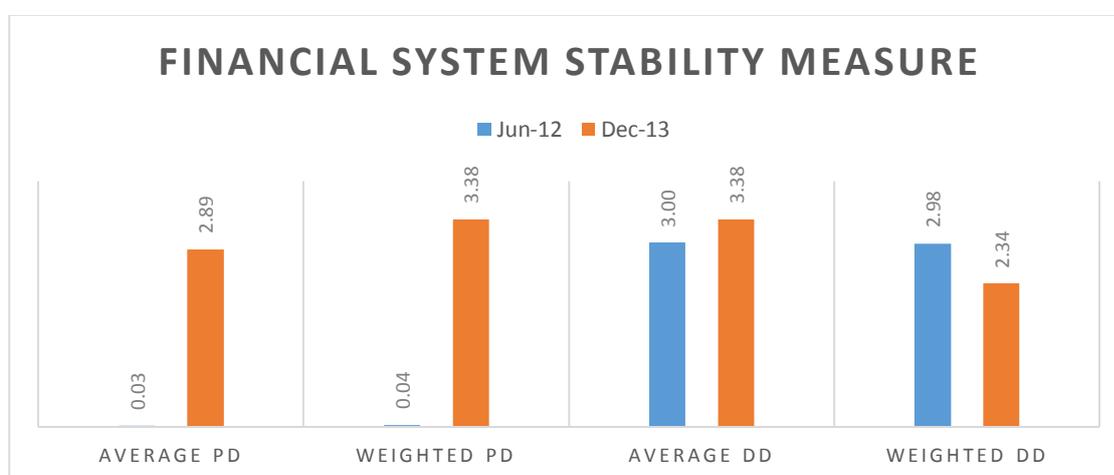


Chart 3 shows that the financial system instability has increased dramatically when analysed based on June 2012 and December 2013 data, using the probability of default risk measure. Based on the PD data, using the probability of default risk measure. Based on the PD measure (Charts 1 and 2, left), it is the Banking, Financial and General Services sectors that caused the instability.

Distance to Distress measure of financial stability (Average DD) has not shown the dramatic decrease in financial stability presented by Average PD. However, there is still a noticeable and clear increase in financial stability from June 2012 to December 2013.

Distance to Distress measure of financial stability (Weighted DD) presents a decrease in financial stability from June 2012 to December 2013, disagreeing with Average Unweighted DD, which can be attributed to

Banking, Financial and General Services sectors instability as depicted by the PD measure.

We expected default risk to be typically higher for banks than for other sectors (higher PDs or lower DDs) given the higher leverage in the banks' balance sheets<sup>3</sup> (owing to their funding with borrowed funds, such as deposits and interbank loans, which have relatively short maturities). The Weighted DD measures confirm this observation and should therefore be adopted for financial system stability analysis because the measure considers each sectoral contribution to systemic risk as fairly as possible.

It is easy to stress a particular firm, a sector or the whole economy based on interest rate, equity price and total capitalisation or other variables so as to enhance financial system stability as estimated using PD and DD.

### **Risk Transmission between sectors**

Risk is easily transmitted between different sectors due to pass-through effects. In the CCA model, it is the implicit put options in risky debts and contingent liabilities, through volatility, that allow for risk to be transmitted between sectors. Without volatility the risk transmission between sectors is lost. The risk-transmission patterns can be dampened or may be magnified depending on the capital structure and linkages.

The manufacturing and services sector's financial distress, which can be caused by stock market decline, commodity price drops, or recession, can be transmitted to the banking sector. The value of the assets of the firms in this sector decline because its collateral value goes down and the expected loss on bank loans together with the value of the debt (and equity). This in turn leads to a decline in bank assets and an increase in banking sector credit risk.

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<sup>3</sup> However, financial intermediaries, like banks, are better capable of bearing certain (complex) risks

Similarly, the manufacturing and services sector's financial distress could cause the funding position of the pension funds to worsen since they invest in the corporate sector. The insurance sector insures the sectors and therefore could also experience a loss. These developments the banking and pension sectors could lead to second-round effects on the economy. A decline in these sectors' assets could cause their equity value to drop. This, in turn, increases the government guarantee to the pension system and the implicit guarantee to banks. As a result of these developments that could lead to the banks' deteriorating solvency, the supply of credit may be curtailed.

Generally, risk is transmitted across the sectors and balance sheets through the implicit put options in risky debts and guarantees (Gray et al, 2008).

## **5.0 Recommendations and Conclusions**

This paper derives default probabilities and distance to default from Merton model and applies this to a number of Nigerian financial and non-financial quoted companies over the period from January 2, 2012 to the December 2013. We argue that this model satisfies the macro-prudential approach to financial system stability analysis. On the basis of the Merton model, we constructed a system -wide financial stability measure for Nigeria, which builds on the put options of the banking, insurance, pension sectors, corporate and manufacturing sectors as traded on the Nigerian Stock Exchange (NSE).

Distance to Distress measure of financial stability (Weighted DD) presented a decrease in financial stability from June 2012 to December 2013, disagreeing with Average Unweighted DD, which can be attributed

to Banking, Financial and General Services sectors instability as depicted by the PD measure. Distance to Distress measure of financial stability should be used for financial system stability analysis by the FSRCC, NDIC, CBN and other related agencies.

Our analysis suggests that the Merton model appears to be useful in ranking sectors according to their contribution to financial system stability. The model also provided a means of measuring financial system stability based on individual firms, sectors and the financial system as a whole using several forward-looking measures.

The key point of this article is that it is useful to look at the financial system as a portfolio of counterparty exposures, the counterparties being financial institutions, and then analyze the contribution of each firm to different sectors and the whole system as a portfolio of firms.

## **Recommendations**

- This analysis was carried out based on only two time periods: June 2012 and December 2013. The FSRCC and NDIC/CBN should carry out this analysis on a quarterly basis so as to *pre-emptively avert, mitigate or manage any potential threat* before it materializes. German central bank (Deutsche Bundesbank ,2005), and Bank Negara Malaysia use this approach as part of their Financial Stability Review. The IMF has also used Contingent Claims Analysis Approach for stress testing exercise of the Financial Sector Assessment Program (FSAP) for Germany, Spain, Sweden, the United Kingdom, and the United States between 2010 and 2012 and the Global Financial Stability (Jobst and Gray, 2013).
- The FSRCC, NDIC, CBN and other stakeholders should initiate or continue enhancing the forward-looking capability of its surveillance

framework by having a more robust assessment of risks in the banking, financial services and corporate sectors in an integrated or holistic manner so as to better enhance the stability of the overall financial system. Forward-looking models, like the Distance-to-Default model used in this paper, should be used in conjunction or as complementary tools to standard regulatory measures to enhance financial system stability.

For instance, Bank Negara Malaysia uses the z-score (based on discriminant analysis) and modified distance to default while *“provide important insights on emerging stress and risks, thereby providing sufficient lead time for the Bank to formulate appropriate policy measures pre-emptively to avert, mitigate or manage such threats. The quantification and measurement of risks enable more robust stress tests to be performed to assess the direct and possible feedback effects from plausible shocks to the system. ...*

*Movements in the median z-score and weighted average modified distance to default are tracked to detect changes in the direction and average level of credit risk both at the macro as well as industry and company specific levels. In addition, Altman z-scores at the 75<sup>th</sup> and 25<sup>th</sup> percentile are also used to monitor the changes in the level of credit risk for firms with higher and lower credit quality, enabling a more complete assessment across different credit qualities.”.*Bank Negara, 2008

Suggested areas requiring further research are as follows:

- Given the varying business characteristics across different firms and sectors, the FSRCC, NDIC and CBN should develop sector specific z-

scores based on the financial statements and default experiences of Nigerian businesses. These stakeholders should map the modified distance to default model to historical incidences of bond and loan defaults by Nigerian businesses, thereby enabling estimates of default probability and frequency to be more reflective of the future level of non-performing loans in the corporate sector.

- The FSRCC, CBN and other agencies can also build a model that incorporates forward-looking measures with macro-economic variables for better measurement of financial system stability. The time pattern of asset returns of each financial institution (or of the risk indicators) can be used as the dependent variable in a factor model. Key factors driving these asset returns could include GDP, domestic and foreign interest rates, exchange rate, domestic and foreign equity indices, etc. A separate macroeconomic scenario generating model, e.g. a macroeconomic vector autoregressive model, could then be used to test the impact of scenarios on the key factors, which feed into the financial institution's assets. This, in turn affects the credit risk indicators and the value of equity capital.
- The NDIC carried out a previous study on measuring systemic risk based on the widely acclaimed SRISK approach pioneered by professors from Stern Business School. Given the complexity of the financial system and its multidimensional nature, the recommendation of using several models simultaneously to measure financial system stability should be considered. The implemented SRISK approach and the DD measures adopted in this paper should be used in tandem for enhancing financial system stability.

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# Appendix

