Modern Finance

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# Measuring the connectedness of the Nigerian banking network and its implications for systemic risk

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**Abstract:** This study examines fifteen major banks' network connectedness in the Nigerian banking system via its stock returns. The paper studies both the static and dynamic network connectedness of banks built on the generalized forecast error variance decomposition, using daily data from January 4, 2005, to June 28, 2019, of publicly traded banks. This study finds a substantial total connectedness, with a high pairwise connectedness among the system's large banks. The dynamic evolution of connectedness in the network reveals that banks' connectivity increases in response to certain economic episodes. The evolution of the global network's topological properties reveals that it is mainly susceptible to shocks threatening its stability. Additionally, the study computes a composite index of systemic importance for the Nigerian banking system by combining several network centrality metrics using the principal component analysis. The outcome shows that large banks are more centralized in the network, and the larger the scale of assets a bank has, the more systemically relevant the bank is in the network. Since systemic risk emanates from connectedness, frequent assessment of the banking system's connectedness and systemic importance will aid policy decisions. The proposed measure of systemic importance can be incorporated into the CBN's stress testing mechanism for fast-tracking risk potential banks.

**Key Words:** Connectedness; Network; Systemic Risk; Stock returns; Banking system

**JEL Classification:** F02, C53, G01

**Citation:** Kamah, M., & Riti, J. (2024). Measuring the connectedness of the Nigerian banking network and its implications for systemic risk. *Modern Finance*, 2(2), 96-119.

Accepting Editor: Adam Zaremba

Received: 21 February 2024
Accepted: 17 November 2024
Published: 22 November 2024



## 1. Introduction

The 2008 global financial crisis and its widely felt worldwide impacts have re-emphasized the relevance of financial institutions' connectedness. Hence, there is a need to evaluate the influence of the feedback loops instilled in the mutual web of exposures connecting financial institutions (De la Concha et al., 2018). As observed during the crisis, the Lehman Brothers and the American International Group (AIG) played a crucial role in amplifying the event through business connections to other institutions. The AIG ultimately received a bailout as it was regarded as too systematically crucial to default. The event revealed that an essential aspect of systemic risk is the transmission of adverse shocks from a single institution to the rest of the institutions in the system, depending on its connectedness and the systemic importance of the shock-originating institution. Hence, to ensure the financial system's stability, analyzing systemic connectedness and identifying and monitoring financial institutions' systemic importance have become crucial for financial regulators in the post-crisis period (Baumöh et al., 2022).

Billio et al. (2012) described systemic risk as a risk that arises from a group of institutions linked by common profitable business associations that can become the medium of disseminating illiquidity, insolvency, and losses during periods of financial turbulence throughout the financial system. That is a shock to the financial system that arises due to the mutual business relationships of financial institutions. Similarly, Diebold and Yilmaz (2014), highlighted the significance of connectedness in assessing systemic risk, as it dominantly features in contemporary risk measurement and management of diverse aspects of risks. Understanding core fundamental macroeconomic risks, such as the business circle, is crucial. Likewise, Gai and Kapadia (2010) stressed that the linkages formed by institutions could be conduits for amplifying or reducing adverse shocks during financial turbulence. Forbes and Rigobon (2002) asserted that connectedness is synonymous with contagion; mainly, it is a substantial rise in market co-movement in reaction to a shock. These definitions bring to the fore the significance of the study of connectedness among financial institutions to ensure stability. It is considered that connectedness can cause substantial disruptions to the overall financial system and economic activities within and outside a border jurisdiction. As witnessed during the 2008 global financial crisis and the European debt crisis, a few recent examples of systemic risk distorted the financial system across broader jurisdictions due to the connectedness of institutions. Understanding the connectedness of institutions will widen the understanding of the dynamics of financial institutions' complex interaction, which is crucial in studying the complex nature of systemic risk. Connectedness can give regulators valuable insights, especially in this post-global financial crisis period due to the shift of financial surveillance from a macroprudential to a more macroprudential approach. The recent global financial crisis revealed the weakness of macroprudential banking regulation. Understanding the links formed by financial institutions will help implement a macroprudential banking regulation successfully. The study of connectedness among financial institutions can also provide meaningful insights that could help regulators identify sources of risks and formulate mediation strategies. Connectedness can also be a helpful guide for investors in making decisions about portfolio diversification to minimize risk Wang et al.(2022), Zhang et al. (2023).

Lately, complex network theory has gained much admiration in modeling connectedness and systemic risk analysis due to the complex interactions among financial institutions. The theory of complex networks seems to provide an appropriate framework for such a large-scale analysis in a representative class of complex systems, with examples ranging from cell biology and epidemiology to the Internet. Besides studying a network's purely structural and evolutionary properties, there has been increasing interest in the interplay between complex networks' dynamics and structure (Motter et al., 2006). In these contexts, time-dependent phenomena are closely related to the system's performance, as illustrated by cascading failures. The nodes could be nonlinear dynamical systems, and the state of each node can vary in time in complicated ways. To this effect, researchers build financial networks to understand the behaviors and dynamics of banks because the banking system has shown itself to be complex with many interactive agents. Some studies that applied the network theory in the analysis of systemic risk and the transmission process of an institution’s risk in a system include Nier et al. (2007), Gai and Kapadia (2010), Upper (2007), Minoru et al. (2013), Diebold and Yilmaz (2014), Martinez-Jaramillo et al. (2014), Guimarães-Filho and Hong (2016) Wang et al. (2022), Das et al. (2022), Zhang et al. (2023).

The literature on systemic risk analysis traditionally focuses on using data from the interbank market and balance sheet information such as non-performing loan ratios, earnings and profitability, liquidity, and capital adequacy ratios. These data are not easily accessible and are primarily available on a relatively low frequency. They are considering the complex nature of systemic risk and the fact that financial institutions are exposed to it through several channels, including the holding of joint assets. Hence, there is a growing effort to measure the systemic risk of a financial system based on data from the stock market, such as stock returns and stock volatilities. This is because stock market data has the merit of easy accessibility and has been updated more timely. This means that stock market data are readily available, unlike granular interbank data, which is readily unavailable due to policy restrictions. Another reason for using stock market data is that they are high-frequency data, making them more informative than low-frequency data. Stock market data incorporate current information and reflect information more rapidly than non-market-based indicators, such as accounting variables. Besides, they are usually forward-looking, in that asset price movements reflect changes in market anticipation on the underlying entities' future performance (Lehar, 2005; Billio et al., 2012; Diebold & Yilmaz, 2009; 2012; 2014; Demirer et al., 2017).

Banks are pivotal financial institutions in a developing economy like Nigeria for their roles in financial intermediation and resource reallocation in an economy. The breakdown of the banking system can be tremendously costly to the financial system and the entire economy, as proven in several financial crises in industrial and developing economies. The interest in the Nigerian banking sector is because of the relevance of the Nigerian economy in the African continent as one of the top three economies and the presence of some Nigerian banks in other African countries. The Nigerian banking system witnessed financial turbulence in 2009, mainly due to the 2008 global financial crisis and during the recent recession/foreign currency crisis arising from the fall in the global crude oil price of 2015/2016. Both events were believed to be systemic and threatened the banking system's soundness, consequent to its connectedness within or outside the financial system. Experiences from the global financial crisis have made monetary regulators respond to the shift from a macroprudential to a more holistic approach. The Central Bank of Nigeria (CBN) has built countercyclical macroprudential policy structures in response to the crises (International et al., 2013). One of the challenges for policy-makers is understanding the connectedness of institutions and how to identify systemically relevant institutions in the banking system.

Another important fact about the banking system in Nigeria is that the banks are generally exposed not only to other common obligors (i.e., their borrowing customers) but also to themselves. For example, banks directly connect via their mutual exposures inherited in the interbank market. Also, the banks are somewhat interconnected via holding similar portfolios and having the bulk of similar depositors. Nigerian banks do not operate as islands; they operate in a system where they interact among themselves and with the international banking system. They perform different kinds of transactions among themselves, and through these transactions, they are exposed to themselves and other everyday obligations. For instance, CBN (2015) statistics show that in the first quarter of 2015, interbank market transactions amounted to N2,809.58 billion, while the unsecured call and tenored transactions stood at N956.63 billion. This explains why it is difficult for any of the banks to collapse in isolation.

Nonetheless, this study's core questions are: To what extent is the Nigerian banking system systemically connected? How does the systemic connectedness of the Nigerian banking system impact the soundness of the banking system? Should we bother about the systemic relevance of banks in the Nigerian banking system? This study seeks to analyze the stability of the Nigerian banking system concerning the connectedness of banks via its stock returns as well as the systemic importance of banks in the system, which is vital in the assessment of systemic risk. This can provide regulators with ideas for making appropriate strategies for monitoring systemically essential banks and improving banks' performances based on risk management in the future.

This study contributes to the literature on connectedness and system risk literature of the Nigerian banking system, an aspect in which the literature is scant. Daily data in this study is also a part of its contribution, as high-frequency data are considered to be more informative than low-frequency data, which other studies in the Nigerian context rely on. It aims to give a broader understanding of banks' systemic connectivity in Nigeria's systemic risk context. This study employed the recently advanced generalized forecast error variance (GFEVD) in Diebold and Yilmaz (2014) to examine banks' dynamic connectedness in the Nigerian banking system. This study also attempts to measure the systemic relevance of institutions in the network by harmonizing six centrality measures using the principal component analysis. Previous studies on systemic risk in the Nigerian banking system neglected the time-varying aspect of systemic events, which is crucial in understanding the dynamic evolution of systemic risk. However, this study incorporated time variability in its analysis and examined banks' interactions based on variance decomposition approximating models from the least to the overall connectedness level. This study also evaluated the interdependence between systemic importance and bank size, as well as the dynamic evolution of the Nigerian banking system. The network connectedness technique applied in this study is diversified as it evaluates the direct connectedness of the banks and estimates the spillover effects from static and time-varying dimensions. This study is different from Diebold and Yilmaz (2014), as the investigation is extended by studying the network's topological properties and systemic relevance examination of the banks under study. It is one of the few studies investigating connectedness and systemic risk in the Nigerian banking system to this extent.

This study finds a substantial total connectedness, with a high pairwise connectedness among the system's large banks. The dynamic evolution of connectedness in the network reveals that banks' connectivity increases in response to specific economic episodes. The evolution of the global network's topological properties reveals that it is mainly susceptible to shocks threatening its stability. Additionally, the study computes a composite index of systemic importance for the Nigerian banking system by combining several network centrality metrics using the principal component analysis. The outcome shows that large banks are more centralized in the network, and the larger the scale of assets a bank has, the more systemically relevant the bank is in the network. The result also indicates that systemic events may change a bank's importance and role in the network. Finally, the outcome of the exponential generalized autoregressive conditional heteroscedasticity Model also suggests the presence of persistent shock in the system.

This paper is subsequently organized thus: following the introduction is the literature review in Section 2. Section 3 describes the methodology and data. Section 4 is the empirical analysis, and lastly, section 5 presents the conclusion and policy implication.

## 2. Literature Review

The empirical studies of connectedness and systemic risk assessment can be categorized into two points of view. The first relies on traditional systemic risk techniques that are not based on the network approach, such as the conditional value at risk (CoVaR), marginal expected shortfall (MES), systemic risk index (SRISK), and others. The second depends on the use of financial network techniques. Some studies that investigated systemic risk using traditional approaches focus on the combined distribution of asset returns and try to evaluate connectedness at the tails of the distribution of returns. For example, Huang et al. (2017) investigated systemic risk in the Chinese banking system by employing the CoVaR, MES, the systemic impact index (SII), and the vulnerability index (VI). The study found that the rankings of banks based on these measures are substantially associated. The result also showed that the systemic risk was reduced after the global financial crisis but rose during the China stock market crash. Kreis and Leisen (2018) evaluated the default across the banking sector in a structural model of individual bank defaults among fifteen US banks. The evidence showed that asset correlation, in a nonlinear way, impacts risk measures of the default frequency in the banking sector. The study also showed that periods of significant correlation coincide with stress (financial distress) periods in the banking sector. Hale and Lopez (2019) proposed a method for assessing connectedness in US banks using the information at the firm level. The study demonstrated how mixed-frequency models could decompose bank outcome variables in network analysis to measure firm connectedness.

Likewise, Verma et al. (2019) adopted the Tail-event-driven NETwork (TENET) risk model to evaluate the systemic risk of Indian banks. The study showed that the Indian banks display high interconnectedness during a crisis. The tail risk outcome revealed that banks are sources of high-risk spillovers in the financial system. Zhang et al. (2020)

examined connectedness and systemic risk spillovers across different sectors in the Chinese stock market. They used the conditional value at risk (CoVaR) and single index model (SIM) quantile regression technique. The outcome revealed that the stock market is exposed to more systemic risk and more connectedness during market crashes. They also found that connectedness is more vital in sector blocks. Guo and Szeto (2017) applied a genetic algorithm to determine the banking network structure, connectivity, bank capitalization, and interbank exposure magnitude. They showed that the network's degree variance should be increased to decrease the systemic risk of a financial system. Leur et al. (2017) investigated the factual content of stock correlation-based network quantifiers for systemic risk rankings. Using European banking data, they showed that correlation-based network measures could supplement the available methods of systemic risk ranking based on book or market values. Manguzvane and Mwamba (2019) modeled systemic risk in the South African banking sector using CoVar. They found that the largest banks pose a more significant threat to the banking system than the smaller banks. Foggitt et al. (2019) analyzed the volatility spillover effect from the US to South Africa using the EGARCH model. They found weak evidence for a direct systemic risk transfer, which indicates that any systemic risk transfer is more likely to take an indirect form through changes in capital flows or interest rates. They also asserted that systemic risk could emanate from variant sources of banks' exposures and that volatility decreases during the global financial crisis in the system.

The second group of literature evaluates systemic risk from the financial network perspective. For example, Billio et al. (2012) used monthly return data to examine United States (US) financial firms' connectedness by principle component analysis and Granger-causality networks. Their results showed that the financial sectors examined connectedness tends to be asymmetric, with banks performing a substantial role in shock propagation. Martinez-Jaramillo et al. (2014) studied the Mexican interbank's systemic risk and the payment system networks based on simulation. They found that a bank's interconnectedness is not certainly linked to the size of its assets but rather related to the contagion it is likely to produce. Diebold and Yilmaz (2014) evaluated US financial institutions' connectedness using networks based on variance decomposition. The study found that connectedness was more vital within similar financial institutions. For instance, a bank tends to be more closely linked to other banks than other institutions in the sample. The study also showed that connectedness increases periods of financial turbulence. Demirer et al. (2017) employed the LASSO methods to shrink, select, and estimate the high-dimensional network linking the publicly traded subset of the world's top 150 banks. They found that equity connectedness increases during crises, with clear peaks during the Great Financial Crisis and after each wave of the European Debt Crisis, and with movements coming primarily from variations in cross-country as opposed to within-country bank linkages. Fang et al. (2018) constructed a tail risk network to present the overall systemic risk of Chinese financial institutions, given the macroeconomic and market externalities. They employed the LASSO method of high-dimensional models. Their results showed that a firm's idiosyncratic risk could be affected by its connectedness with other institutions. Pelton et al. (2018) used the macro-network to evaluate the banking sector's linkages related to European banking crises. They found that as the banking sector occupies a key position, the macro-network substantially increases the possibility of a banking crisis. Their evidence from the analysis of various risk sources shows that credit is a crucial medium of fragility. They also showed that early-warning models combined with interdependency measures surpassed conventional models in out-of-sample predictions. Leur et al. (2017) investigated correlation-based network quantifiers for systemic risk rankings of European banking. The study revealed that correlation-based network measures could supplement the available methods of systemic risk ranking based on book or market values. Other studies on systemic risk and connectedness of the banking sector tried to propose measures for predicting systemic risk, including (Baumöh et al., 2022; Das et al., 2022; Wang et al., 2022; Zhang et al., 2023).

Narrowing down to the literature on system risk analysis in the Nigerian banking sector, little work has been done. Nakorji et al. (2017) assessed Systemic Risk in the Nigerian interbank money market based on network simulation of default contagion, using annual data from the interbank market. They found that banks' exposure to systemic risk depends on their capital. Fan et al. (2018) analyzed the capital requirements in managing systemic risk in Nigeria under a heterogeneous macroprudential capital requirement. The outcome showed that their proposed risk allocation mechanisms considerably reduce systemic risk. Nonetheless, the literature on connectedness and systemic risk in the Nigerian banking sector is scant. The related studies in the Nigerian context have some limitations: The previous studies on system risk in the Nigerian banking system focused on point analysis. The studies failed to incorporate a time dimension to evaluate system risk, considering that systemic events are granular events that spark off over time and are amplified by connectedness in the system. The time-varying evaluation of connectedness and systemic risk cannot be overruled. Besides, the previous studies failed to analyze the systemic relevance of banks to check the influential banks in the system. Lastly, their choice of using annual data limits the validity of their outcome because low-frequency data are less informative than high-frequency data. Data and an undiversified approach to analyzing systemic risk weaken the outcome of the previous studies. The limitations of the previous studies on connectedness and systemic risk in the Nigerian banking sector motivate this study.

## 3. Methodology

The study adopts the financial network theory in assessing the behaviors and dynamics of banks. This can provide helpful information about the connectedness and systemic importance of banks. This study adopts the network connectedness measures based on the H-step-ahead generalized forecast error variance decomposition (GFEVD) to analyze the spillover of stock returns of publicly traded banks in Nigeria. Diebold and Yilmaz (2014) proposed and advanced these measures of connectedness by employing the "generalized identification" architecture of Koop et al. (1996) and Pesaran and Shin (1980). The approach effectively marries the vector autoregression (VAR) variance decomposition and network topology theories. Thus, recognizing that variance decompositions of VARs form weighted directed networks, characterizing connectedness in those networks and, in turn, characterizing connectedness in the VAR. GFEVD are attractive because they provide the primary solution for quantifying at the most granular pairwise level the future uncertainty of an institution (at horizon H) emanates due to shocks from other institutions in a system other than from itself. GFEVD as a technique of estimating connectedness is tightly related to contemporary network postulations and the different systemic risk measures, such as marginal expected shortfall by Acharya, Pederson, Philippon & Richardson (2017) and CoVaR by Adrian and BrunnerMeier, 2016 (see Diebold and Yilmaz, 2014 for proof). GFEVD is helpful in the measurement and management of risk. Since it is linked to MES and CoVar, it is implicitly also linked to stress testing because the conditioning in MES and CoVaR amounts to conditioning on stress scenarios. The GFEVD connectedness technique is a more diversified approach to studying systemic risk. It reveals the static and time-varying connectedness, which can help us understand financial cycles and build a countercyclical policy framework for financial stability.

### *3.1. Connectedness Measures (Network construction)*

Bank's contribution to Bank's H-step-ahead generalized forecast error variance is:

$$d_{ij}{}^{gH} = \frac{\sigma_{jj}{}^{-1} \sum_{h=0}^{H-1} (e_i^{'} \Theta_h \Sigma\, e_j)^2}{\sum_{h=0}^{H-1} (e_i^{'} \Theta_h \Sigma\, \Theta_h^{'} e_i)}, \quad (1)$$

where Σ is the covariance matrix of the disturbance vector $\varepsilon$, $\sigma_{jj}$ is the standard deviation of the disturbance of the *j-th* equation, and $e_i$ is the selection vector with one as the *i-th* element and zeros otherwise.

*3.2. Network centrality measures*

The centrality of nodes is a cardinal issue in network analysis and is likely translated as power, influence, independence, control, etc. (Freeman, 1979). The centrality values of various nodes are dissimilar in a network because some nodes are more central and have strong connectedness with other nodes. While, some nodes are at the brink of the network and have frail connectedness with others. This study adopts six centrality measures primarily used in financial network analysis: degree centrality, strength centrality, betweenness centrality, closeness centrality, eigenvector centrality, and PageRank centrality.

(1) Degree centrality

It refers to the number of links (edges) going out and coming into a node in a network. Banks with more links out of it may be better placed because they can directly impact more banks in the network analysis context. Degree centrality ($D_c$) Is the sum of the *i-th* row and column in the adjacency matrix *A*. The definition is:

$$d_i = \sum_{j \in N(i)} a_{ij}. \tag{2}$$

(2) Strength centrality

The total strength of a node, v, is the aggregation of its "from" and "to" connectedness. A node's total strength is a simple but essential measure. It can be described as an intensity-of-interaction measure. The strength centrality ($S_c$) A node in the network is defined as:

$$s_i = \sum_{j \in N(i)} w_{ij}. \tag{3}$$

In addition, total, inner, and outer strength are relevant measures because they could be useful in determining whether a bank plays a more important role as a risk contributor or a risk receiver in the network.

(3) Betweenness centrality

Betweenness centrality measures how often a node acts as a pathway along the shortest path between two other nodes. If the betweenness centrality of a bank is more extensive, it suggests that it plays a vital role in transporting stock return spillover. Let $\sigma_{ij} = \sigma_{ji}$, the total number of shortest paths between i and j. And let $\sigma ij(v)$ be the total number of the shortest paths between *i* and *j* that pass through the vertex *v*. Betweenness centrality ($B_C$) It is defined as:

$$C_B(v) = \sum_{i \neq v \neq j \in V} \frac{\sigma_{ij}(v)}{\sigma_{ij}}. \tag{4}$$

(4) Closeness centrality

In the systemic risk and financial contagion context, this measure can be linked with a bank's ability to spread shocks, as a bank is close to the rest of the nodes in the network. Closeness centrality ($C_c$) is defined as

$$C_C(i) = \sum_{j \in \forall \setminus \{i\}} \frac{n-1}{d_G(i,j)}, \tag{5}$$

in which $d_G(v,j)$ denotes the length of the shortest path that joins *v* and *j*.

(5) Eigenvalues centrality

This measure takes into consideration the centrality of the neighbors to compute the centrality of a node. Bonacich (1972) states that It considers the direct and indirect connections. Hence, this measure considers "the entire network pattern" in a weighted sum. This matrix is the weighted adjacency matrix, *W*. The Eigenvector centrality ($E_C$) for node *i* is $AX = \lambda X$. Let *X* be the eigenvector of the largest eigenvalue $\lambda$ of the adjacency matrix $A$. By the Perron–Fresenius theorem, there is a peculiar and positive solution if $\lambda$ *i*s the maximum eigenvalue linked with the eigenvector of the adjacency matrix $A$.

(6) PageRank centrality

This measure considers the importance of neighboring nodes in deciding the relevance of a node in the network. PageRank (*PRc*) Centrality is based on Google's algorithm proposed in Page et al. (1999), which considers the World Wide Web (WWW) as a digraph. The algorithm used to calculate the PageRank centrality was proposed by Langville and Meyer (2006). It is denoted as

$$C_P(i) = \sum_{i,j\in N(i)} \frac{C_P(j)}{O_j}, \tag{6}$$

where $Q_j$ is the number of out-links from *j*.

(7) A unified measure of centrality

In order to reduce information loss by using only a single centrality measure as a metric for assessing the systemic importance, and because each centrality measure looks at a different aspect of a network. This study employs the principal component analysis (PCA) to harmonize the centrality measures to a composite metric computed for each bank separately. The proposed composite measure would be a linear harmonization of the standardized scores of the six centrality measures because centrality measures are often quantified in different units. Following Martinez-Jaramillo et al. (2014), we employ the PCA to compute a composite centrality metric, defined as;

$$PC = \alpha_1 D_c{}^* + \alpha_2 S_c{}^* + \alpha_3 B_c{}^* + \alpha_4 C_c{}^* + \alpha_5 E_c{}^* + \alpha_6 PR_c{}^*. \tag{7}$$

We use the PCA to select the coefficients of equation (7). This approach provides a benchmark for obtaining an optimal linear combination. The new components created keep most of the information provided by the centrality measures considered.

The study uses the EGARCH approach for robustness to confirm the dynamic existence of shock spillover in the system. Nelson's (1991) proposed the EGARCH with the conditional variance defined as:

$$\ln h_t = \vartheta + \sum_{j=1}^{q} \delta_1 \left|\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}}\right| + \sum_{j=1}^{q} \theta_j \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} + \sum_{j=1}^{p} \varphi_1 \ln(h_{t-1}), \tag{8}$$

where $\vartheta$, $\delta$, and $\varphi$ are the parameters that are to be estimated. Since the variance ($h_t$) is taken in logarithmic form. The leverage effect will be exponential as opposed to quadratic. The parameter $\vartheta$ is essential when testing for asymmetries because θ1=θ2=…=0 would signify the model is symmetric. $\vartheta < 0$ implies that positive shocks generate lesser volatility than adverse shocks (Asteriou & Hall, 2011). $\delta$ *m*easures the impact of innovation on the conditional variance at time *t*, while $\varphi$ is the shock persistence parameter.

### *3.3. Data*

This study employed daily data in the empirical analysis to overcome the lack of bilateral granular data exposure availability, which is not always readily available. We obtained daily stock prices from the Nigerian Stock Exchange (NSE) for the current study, covering the period from January 4, 2005, to June 28, 2019. The study period began in the year 2005, at the time the Nigerian banking sector witnessed a significant policy change, known as the reconsolidation and recapitalization policy whose aim is to strengthen the banking sector and prevent systemic risk. Prior to the reform, the banking system's effective performance was limited. Several structural operational inadequacies characterized it, such as a low capital base, heavy reliance on public sector deposits, weak corporate governance, and unethical and professional practices. At the birth of this policy, many banks rushed to the NSE in search of funds due to the restriction on banks' reliance on government patronage. Before the reform period, only seven banks out of the 15 sampled banks were listed on the exchange, and others joined as time elapsed. The study period covers the prominent bank consolidation policy, the global financial crisis, the recent foreign currency crisis, and the recession in Nigeria. We employed market data with higher frequency, which can reflect current information about the financial system more rapidly. Following Lehar (2005), Diebold and Yilmaz (2012), Billio et al. (2012), and Guimarães-Filho and Hong (2016), we transformed the data into stock. Returns are thus defined as:

$$R_t = ln(p_t/p_{t-1}) \times 100\%, \quad (9)$$

where, $R_t$ are the returns, logarithm, $p_t$ denotes the price at time t. The population of the study is the 23 money deposit banks in Nigeria, of which only 16 are publicly traded. We study 15 major commercial banks publicly traded on the Nigerian stock exchange based on data availability. The names of the banks and their acronyms are listed in Appendix A. For simplicity, we will work with the acronyms. Connectedness from stock returns data has the merit of revealing the shocks to the system in both crisis and non-crisis periods (Diebold & Yilmaz, 2014).

## 4. Empirical Network Connectedness Analysis and Discussions

We begin the discussion by describing the network and its characteristics, then move to the systemic relevance analysis and implications.

### 4.1. Connectedness of the Nigerian Banking System Network

We present the static and dynamic connectedness of the Nigerian banking system and interpretations given concerning system events in the economy. The GFEVD estimates are obtained from the VAR approximating model at a horizon of 10 days. The width for the rolling window analysis is 60 days for the dynamic analysis, an interval wide enough to reveal quarterly shocks.

#### 4.1.1. Full-Sample and Unconditional Analysis

Table 1 shows the static and unconditional connectedness matrix among the 15 Nigerian banks under study. The *i*-th and *j*-th entries in each panel are estimated contributions to the forecast-error variance of bank *i* coming from bank *j*. The estimated contribution to the variance of the forecast variance error of bank *i*, coming from innovations to the bank, is referred to as the pairwise directional connectedness. The diagonal elements (*i*=*j*) are the proportion of the forecast error variance of bank *i* that is from its shocks. In contrast, the off-diagonal elements present spillover from the stock returns of other banks. The column "From" shows the total connectedness or spillover effects received by a particular bank from all other banks. In contrast, the " To " row shows the spillover effects directed by a specific bank to all other banks. The lower right corner, "Total," indicates the level of total connectedness or system-wide connectedness, that is, the average of the sum of "To" or "From" connectedness. The estimates in the row named "Net" indicate the net pairwise directional connectedness, which is obtained by subtracting the "From" connectedness from the "To" connectedness. A negative value indicates a net recipient, and a positive value indicates a net transmitter of shocks.

It is notable from the full-sample (static) connectedness table that a block of high pairwise directional connectedness appears among the top 5 banks under study. The diagonal elements and their connectedness tend to be the most significant individual elements of the table. However, total directional connectedness (from others or to others) tends to be much larger. Besides, the spread of the ''from'' degree distribution is noticeably less than that of the ''to'' degree distribution. It is because a shock from a bank hits it first before it disperses to others in the system.

The pairwise directional connectedness measures are the off-diagonal elements of Table 1. The highest observable pairwise connectedness is from ZEN to GTB (13.66%), and in return, the pairwise connectedness from GTB to ZEN (13.1%) is the second-highest. Another high pairwise directional connectedness is from UBA to ZEN (12.51%) and GTB to FBN (12.13%). These banks with the most extensive pairwise connectivity are among the top 5 banks in the system, so it is reasonable that their pairwise connectedness measures are relatively high as competitors. The close relationship among the top banks implies that the network is likely contagious if one is distressed. Thus, a bank may be too big to fail but not too connected to fail. Pairwise directional connectedness of other banks in the network tends to be much lower than that of the top 5 bank stocks. It means that their influence in the network is minimal. Most of the lower banks in the network have higher diagonal elements that are "own connectedness," which indicates big internal shocks. The internal shocks could be due to factors affecting bank performance, such as operational policies. For example, SKY has the largest own connectedness (58.35%). This bank was distressed during the currency crisis and sold to another bank. Next is DIA (46.59%), which was later acquired. FBN is the net transmitter (49.31%), and FID is the system's net receiver (-32.26%). Other banks with high positive net values are GTB (39.14%), UBA (31.15%), and ZEN (26.21). It suggests that the big banks are transmitting most of the shock spillover in the network. Finally, the total (system-wide) connectedness is 59.67%. It indicates that the network's overall spillover effects are high because the Nigerian banking system is still evolving and may strengthen with more liquidity. As seen from Table 1, most of the big banks in Nigeria, in terms of assets, like Guaranty Trust Bank, First Bank, UBA, Zenith Bank, and have high pairwise connectedness. Individually, they can be regarded as too big to fail in this context. However, the presence of high pairwise connectedness between these banks can lead to "too connected to fail." This is because a negative shock from one big bank, say Guaranty Trust bank, can spread to other banks, meaning that if the entity failed due to its size, exposure to counterparties, liquidity position, interdependencies, role in critical markets, or other factors, it would have a catastrophic effect on the economy, as witnessed during the financial crisis of 2007 in the USA.

Figure 1 summarizes the pairwise directional connectedness among the pairs of banks under consideration. The arrows' different-colored shading marks the degree of strength of pairwise interdependence. The arrow shaded with black indicates a close relationship, while blue signifies a weak relationship.

For example, in Figure 1, the stock returns of ZEN are tightly connected to that of GTB and all other banks marked with a thick black arrow, which implies banks with close connectedness. Similarly, the thin blue arrows refer to banks with lower network connectivity. However, all the nodes in the network are connected but with varying weights of connectivity. It is noticeable from the table that a few nodes are highly connected with large forecast error variance values, while others have low connectedness. High pairwise directional connectedness exists among the big banks and some medium banks, while small banks have lower connectivity. This signifies that the network displays a scale-free property with few highly connected nodes and low connectivity of most nodes.

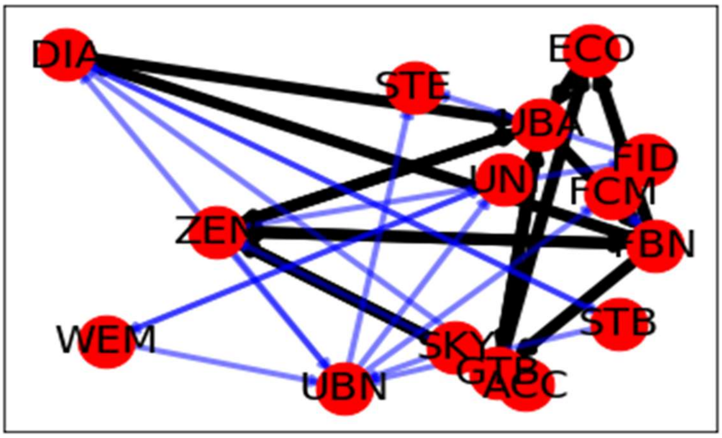
**Table 1:** Stock returns connectedness.

| | ACC | DIA | ECO | FBN | FCM | FID | GTB | SKY | STB | STE | UBA | UBN | UNI | WEM | ZEN | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ACC | 32.09 | 5.6 | 10.29 | 10.77 | 2.28 | 2.63 | 8.7 | 1.96 | 1.33 | 2.17 | 7.77 | 4.68 | 1.49 | 1.37 | 6.87 | 67.91 |
| DIA | 1.66 | 46.59 | 4.72 | 8.52 | 1.43 | 2.22 | 5.63 | 2.32 | 2.37 | 2.15 | 9.12 | 2.57 | 1.89 | 2.04 | 6.77 | 53.41 |
| ECO | 3.86 | 2.3 | 36.88 | 11.39 | 1.74 | 3.05 | 11.98 | 3.24 | 2.17 | 3.12 | 10.42 | 2.28 | 1.46 | 1.21 | 4.9 | 63.12 |
| FBN | 2.58 | 10.14 | 3.19 | 33.27 | 1.51 | 1.09 | 12.13 | 1.7 | 2.08 | 1.27 | 11.78 | 4.13 | 1.99 | 1.69 | 11.45 | 66.73 |
| FCM | 4.33 | 4.06 | 5.01 | 8.22 | 44.96 | 2.14 | 6.74 | 2.69 | 1.76 | 1.35 | 5.03 | 2.27 | 1.67 | 2.79 | 6.98 | 55.04 |
| FID | 2.2 | 6.15 | 5.51 | 5.27 | 3.33 | 35.26 | 8.3 | 3.51 | 2.77 | 4.17 | 5.37 | 3.49 | 2.45 | 2.57 | 9.65 | 64.74 |
| GTB | 2.87 | 2.85 | 7.86 | 12.06 | 1.38 | 2.22 | 34.14 | 1.42 | 2.42 | 1.89 | 10.47 | 3.63 | 1.64 | 1.49 | 13.66 | 65.86 |
| SKY | 3.09 | 3.01 | 2.94 | 2.73 | 4.52 | 3.26 | 2.5 | 58.35 | 2.19 | 4.67 | 1.22 | 2.98 | 3.76 | 3.35 | 1.43 | 41.65 |
| STB | 2.21 | 3.51 | 10.35 | 10.72 | 4.63 | 1.24 | 3.47 | 4.1 | 42.76 | 3.76 | 2.48 | 1.52 | 3.25 | 1.57 | 4.43 | 57.24 |
| STE | 3.33 | 2.51 | 4.5 | 4.93 | 1.92 | 3.47 | 5.09 | 2.88 | 3.73 | 45.65 | 3.41 | 5.29 | 4.12 | 3.63 | 5.54 | 54.35 |
| UBA | 2.91 | 10.59 | 2.65 | 11.81 | 0.92 | 1.56 | 12.74 | 1.43 | 1.25 | 2.31 | 35.68 | 2.25 | 1.95 | 1.51 | 10.44 | 64.32 |
| UBN | 1.41 | 4.65 | 8.51 | 8.88 | 1.94 | 1.25 | 6.16 | 1.83 | 2.89 | 4.87 | 10.75 | 37.08 | 1.63 | 1.25 | 6.9 | 62.92 |
| UNI | 4.76 | 2.38 | 3.57 | 6.06 | 3.91 | 2.32 | 4.85 | 2.62 | 3.96 | 2.75 | 2.93 | 4.46 | 44.03 | 9.75 | 1.65 | 55.97 |
| WEM | 3.43 | 2.93 | 5.95 | 2.62 | 5.76 | 4.41 | 3.61 | 3.02 | 3.82 | 4.16 | 2.21 | 3.66 | 5.28 | 45.87 | 3.27 | 54.13 |
| ZEN | 4.68 | 2.23 | 4.96 | 12.06 | 1.79 | 1.28 | 13.1 | 2.41 | 1.2 | 2.89 | 12.51 | 3.21 | 2.42 | 2.99 | 32.27 | 67.73 |
| TO | 43.32 | 62.91 | 80.01 | 116.04 | 37.06 | 32.14 | 105 | 35.13 | 33.94 | 41.53 | 95.47 | 46.42 | 35 | 37.21 | 93.94 | 895.12 |
| NET | -24.6 | 9.5 | 16.89 | 49.31 | -18 | -32.6 | 39.14 | -6.52 | -23.3 | -12.8 | 31.15 | -16.5 | 21 | -16.92 | 26.21 | 59.67% |

*Source*: Researchers' computation.

*Note:* ACC =Access bank; DIA = Diamond bank; ECO = ECObank; FBN = Firstbank; FCM = First CityMonument bank; FID = Fidelity bank; GTB = Guaranty Trust bank; SKY = Skye bank; STB = Standard Trust bank; STE = Sterling bank; UBA = United Bank for Africa; UBN = Union bank; UNI = Unity bank; WEM = Wema bank; ZEN = Zenith bank

**Figure 1:** Network results




4.1.2. Estimation of Dynamic Connectedness in the Nigerian Banks System

In estimating the time-varying (dynamic) connectedness, we employed the rolling estimation window analysis. This approach has the tremendous merit of being easy to understand and consistent with various possible fundamental time-varying parameter mechanisms. As stated earlier, the predictive horizon, $H$=20 days, and the rolling estimation window of width w=60 days will be maintained throughout the study.

The discussions for dynamic connectedness will start in the reverse direction from the total or system-wide connectedness and then proceed to the net pairwise directional connectedness.

**Figure 2:** System-wide connectedness or total connectedness

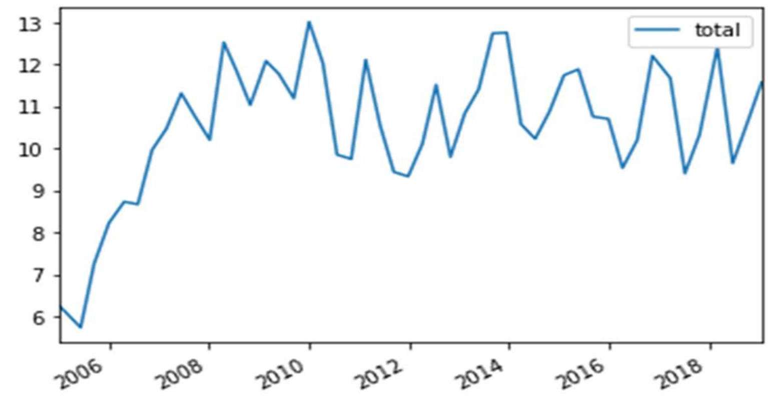



Figure 2 shows the dynamic evolution of the system-wide connectedness. The peaks on the graph indicate an increase in connectedness resulting from shocks in the system. Notably in 2009, during the Nigerian banking crisis, and around 2010, as a result of the recession in the Nigerian economy. Both events can be attributed to shocks in the system from the global financial crisis and the aftermath activities, such as the fall in crude oil prices. Around 2013/2014, there is another rise in connectedness resulting from policy changes in the banking sector by the Central Bank of Nigeria in furtherance of its financial deepening agenda, such as the cashless banking policy, financial inclusion, implementation of international financial reporting standards (IFR), risk-based supervision and sustainable banking. In this case, the increased stock returns connectedness resulted from a positive externality from the policy change. The policies' implication resulted in boosting the financial sector performance; as emphasized in the Nigerian stock exchange outlook (2013), almost all market indices exceeded their performance pre-global financial meltdown.

**Figure 3:** Rolling Net Directional Connectedness.


The increase in connectedness between 2017 and 2018 is due to the Nigerian foreign currency crisis and recession resulting from the global crude oil price fall in 2016. The Nigerian economy slowed down during this period (2016-2018). Banks struggled to survive because some invested in the petroleum sector. With the crash in crude prices, lousy debt increased due to some banks' inability to drawback loans granted to the oil industry. Again, banks could not meet their customers' foreign currency demands due to the CBN's inadequate foreign exchange reserve during this period. This further slowed the economy for an import-dependent economy, which is mono-structured like Nigeria, which depends heavily on crude oil export for its foreign reserves.

Figure 3 presents the evolution of net directional connectedness for each of the respective banks. The style of variation in the "net" directional spillover may differ over the sample period. This is because individual firms' stock responds differently to idiosyncratic shocks due to differences in operational factors before such shocks are being passed to other stocks in the system.

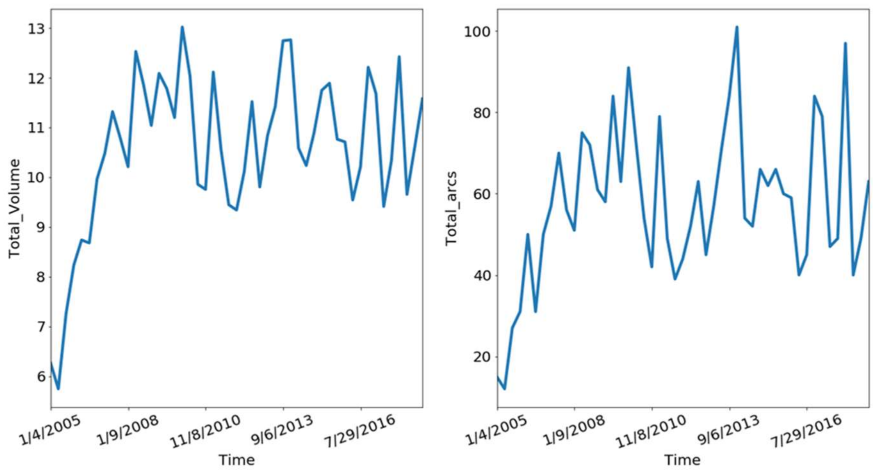
### *4.2. Dynamic Analysis of the Global Topological Network Features Nigerian Banking System*

In this subsection, the study follows (Martinez-Jaramillo, 2014) to give the description of the dynamic evolution of some basic global topological properties of a network. This is mostly used in financial network analysis was employed to assess network connectedness in the Nigerian banking system. The global measures describe the network as a whole, whereas the individual measures describe banks individually. In this work we will only report global measures as the individual ones are difficult to present due to confidentiality constraints.

#### 4.2.1. Volume and total arcs

Figure 4 depicts the evolution of the total of the off-diagonal entries in the connectedness table. It is equal to the sum of the "from" column. In other words, the volume of our stock returns spillover network is the time-varying system-wide connectedness of stock returns of fifteen banks in the network. The volume is a metric that can reveal the extent to which the banking system is internally interconnected through its outflow or inflow of spillovers (shocks) in the network. It is similar to world exports or imports in international finance. While the number of links or edges denote the number of total arcs in the studied network. The arcs are channels via which externalities such as the risk of contagion in the network can spread in crisis periods. It is a metric used to assess the robustness of the entire system.

**Figure 4:** Evolution of the banking system network (a) the sum of "from" (volume) (b) the total arcs




It is observable that both plots have a jump around 2006, which signifies an increase in both the volume and total arcs. It coincides with the period of the full implementation of the 2005 bank recapitalization policy in Nigeria. During this period, the system saw new entrants as more banks rushed to the stock market in search of funds to meet the capital requirement. The curve's dwindling feature is a sign of response to shocks, resulting in an increase or a reduction in the system's connectedness. The peaks on the plots signify periods of high connectedness, while the trough symbolizes periods of decrease in connectedness in response to shocks. As noted earlier, the Nigerian banking system's volume and total arcs reveal that the network is unstable and susceptible to foreign and domestic shocks attributed to the Nigerian banking crisis, foreign currency crisis, and recession periods. This result is consistent with Diebold and Yilmaz (2014), Verma et al. (2019), Demirer et al. (2017), and Zhang et al. (2020).

4.2.2. Completeness index and the average degree

A graph's Completeness Index (CI) compares how close a graph is to the complete graph with each pair of nodes connected. The entire graph has an index of 1, whereas the graph with no edge has an index of 0. It is related to network density and gives a picture of the extent of node connectivity in the network.

**Figure 5:** The evolution of the banking system Completeness index

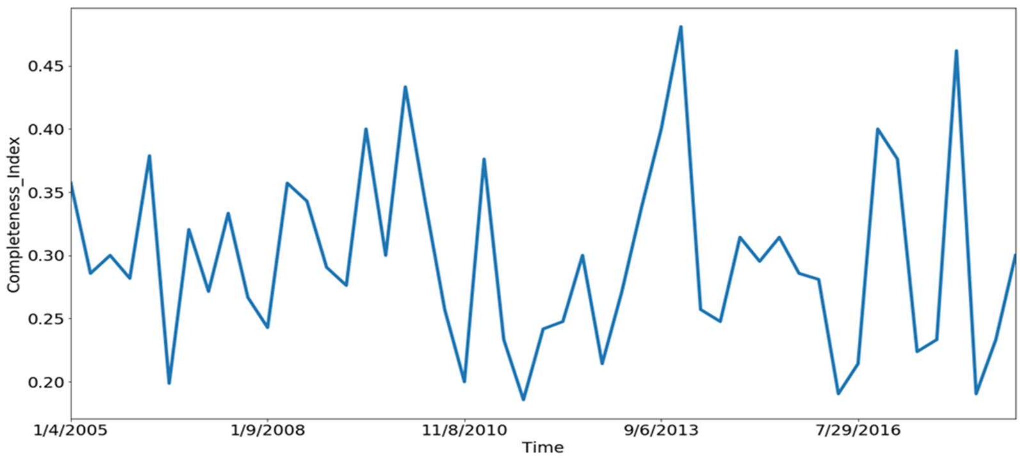
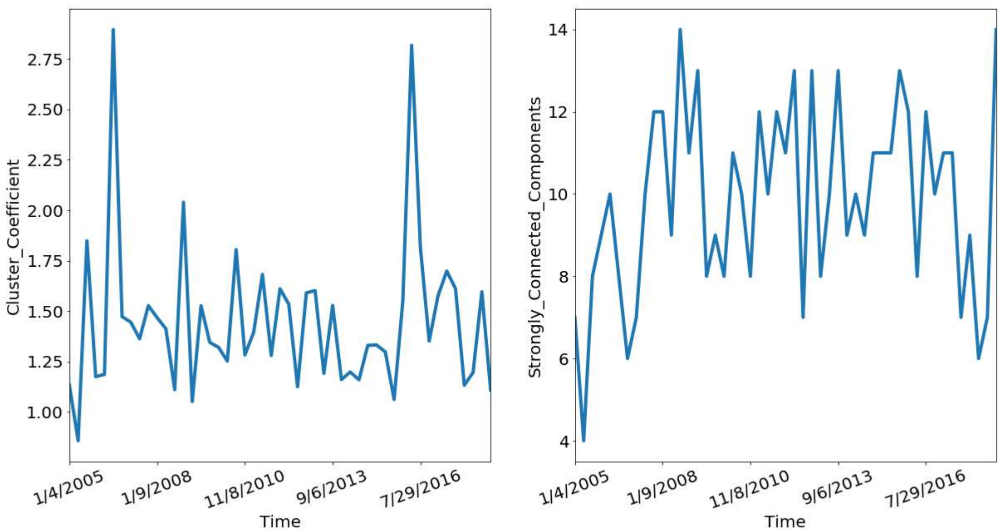



Figure 5 shows the evolution of the completeness index in the network under study. Connectivity increases during shocks and is low at regular times. The completeness index, observable from the graph, is close to 0.5. The connectedness of stock returns is moderately dense because only a group of nodes are closely linked. The peak periods correspond to periods of financial distress and also signify high connectedness periods. As time varies, this network becomes more unstable in response to shocks.

4.2.3 Clustering coefficient and strongly connected component

The clustering coefficient metric can measure the tendency for triangles of connections in the banking system network; that is, the degree to which nodes in a graph tend to cluster together. The relative clustering coefficient is calculated by dividing the banking network's average Clustering Coefficient (CC) by the random graph with the same number of nodes and average degree. Figure 6(a) shows that the relative CC index is greater than one throughout the study period, which implies that the stock returns network deviated from a random graph and tends to possess more triangles than a random graph. It can also be interpreted as a high degree of circulation of shocks among cliques in the network, as indicated in Table 1 (strong connectedness among certain banks).

**Figure 6:** The evolution of the banking system (a) Relative clustering coefficient (b) strongly connected component.

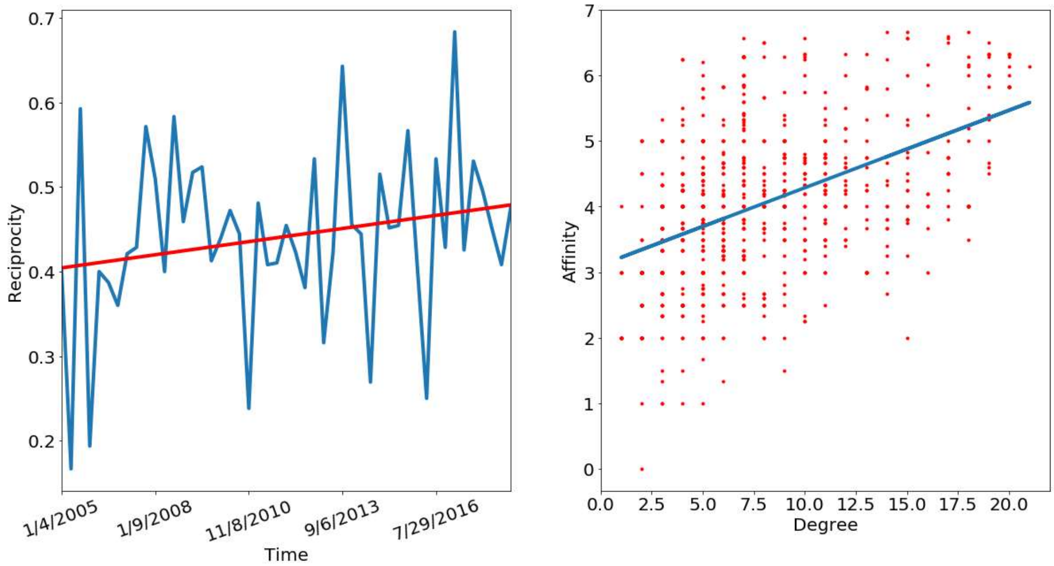



The giant strongly connected component (GSCC) or core is the most significant component; for each pair of nodes i and j, a path exists from i to j and a path from j to i (Dorogovstev et al., 2001). Figure 6(b) shows the strongly connected component of the network. It is observable that the network dwindles throughout the study period. This implies that the paths between nodes in the network are not stable. This coincides with more connection during turbulence and less connectedness in tranquil times. It is similar to the findings in Martinez-Jaramillo et al. (2014).

4.2.4 Reciprocity and assortative mixing

A directed graph's reciprocity is the fraction of the number of links pointing in both directions to the aggregate number of connections. Figure 7(a) shows the reciprocity of the Nigerian banking system network. From the reciprocity graph, we can infer that the reciprocity is around 44%, which implies that close to half of the network nodes are linked bilaterally. This measure significantly interprets the speed and mechanism of contagion in case of any spillovers. Assortative mixing (affinity vs. degree) can be used to assess the structure of a social network. It occurs when the nodes with similar connect characteristics. For example, the network is disassortative if low-degree nodes are linked to high-degree nodes. Figure 7(b) shows that the Nigerian banking system exhibits an "assortative mixing" incidence, which means that the counterparts of highly connected nodes are high-degree nodes, as suggested in the static connectedness analysis where big banks link more to big banks in the system. This contrasts with the findings of Martinez-Jaramillo et al. (2014).

**Figure 7:** Evolution of the banking system network (a) Reciprocity. (b)Affinity vs. Degree




*4.3. Centrality and Systemic Importance Analysis*

The composite centrality measure is referred to as the principle component (PC) measure and is used to analyze banks' systemic importance in this study. The PC measure for each bank is ranked to obtain its position in the network at a certain period. The higher the node's ranking is, the more central (systemically important) it is in the network. This result has a significant interpretation for determining systemic relevance in studying systemic risk. The dynamic evolution of the principle components (PC) metric ranking and the rankings of the centrality measures for some of the banks in the network show that both the principle component ranking and the rankings of the six centrality measures of the banks vary randomly with time, in response to changes in economic events. For example, in Figure 8, ACC rankings of the six centrality measures change as time varies, and the PC ranking changes. This means that a bank does not maintain a fixed ranking throughout the study period and does not have the same ranking in all the centrality measures. In 2009, ACC ranked first based on the PC ranking and ranked 14th and 8th on degree centrality and betweenness centrality measures, respectively. Since the centrality rankings of a bank change over time, it becomes apparent that a single centrality measure cannot be used as a measure of systemic importance. Thus, there is a need for a systemic relevance metric that can incorporate more information, such as the proposed composite measure. Systemic events play an indispensable role in determining ranking in this banking network.

**Figure 8:** Centrality ranking for ACC

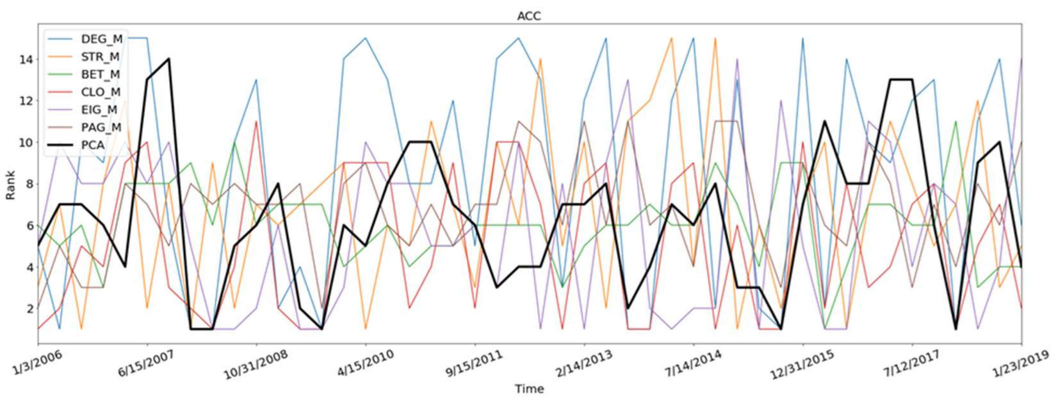
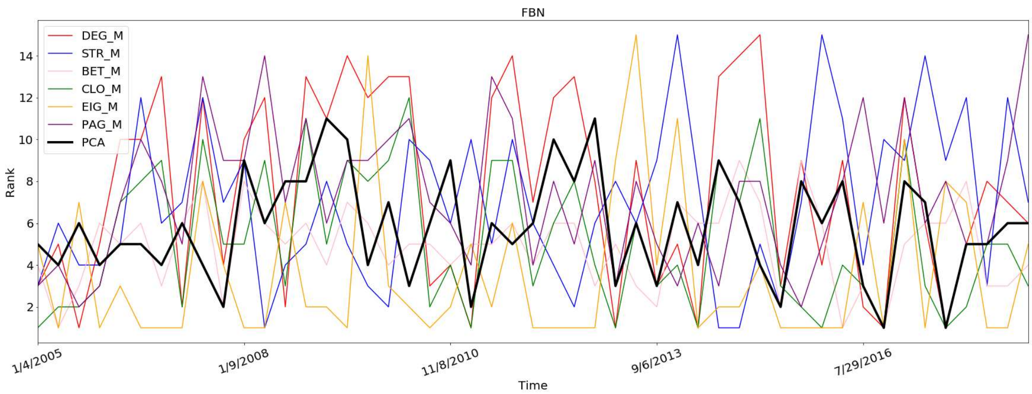


Figure 9 shows another distinct feature of the banks as regards their systemic importance. The PC centrality ranking for FBN reveals that it is a good market regulator because it maintains a high PC centrality during crisis periods and low ranks in tranquil times. During the Nigerian banking crisis in 2009, it ranked high, as well as in 2016, during the foreign currency crisis and the recent recession in 2018. In tranquil times, it mainly maintains a low centrality rank. Subsequently, the principal components centrality measure would be solely used in analyzing the Nigerian banking system.

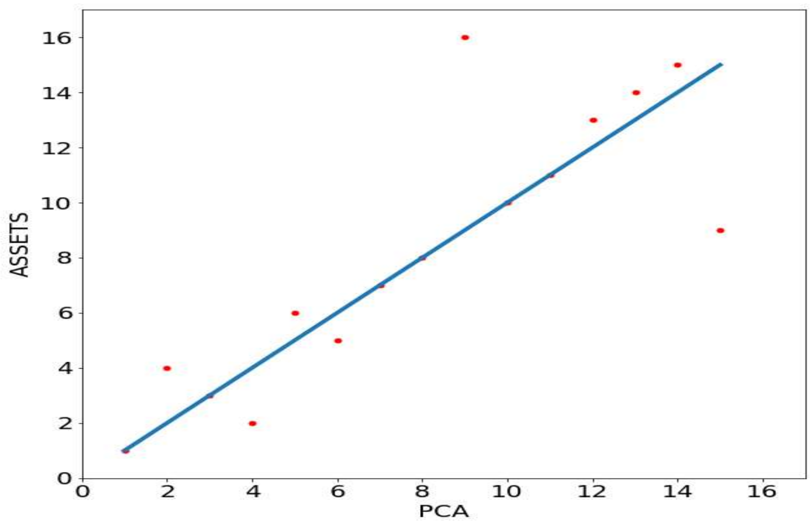
**Figure 9:** Principal components centrality and the corresponding ranking of centrality measures.




4.3.1. Bank Size and Systemic Importance

In this subsection, the PC ranking is the proxy for systemic importance, while banks' ranking according to their asset size is the proxy for bank size. Figure 10 shows the PC ranking against the assets ranking. The assets ranking is sorted by the average rank of a bank's assets over the entire study period. Rankings provided by the PC measure are highly related to the asset size ranking for most banks in the system, and the correlation between them is about 0.91. It implies that the size of a bank's ranking can indicate its systemic relevance in this network; the more assets banks own, the more central they are. The size of can bank influences its systemic risk contribution. This outcome is related to Kreis and Leisen (2018) and Manguzvane and Mwamba (2019); other studies that prove the contrary include Martinez-Jaramillo et al. (2014).

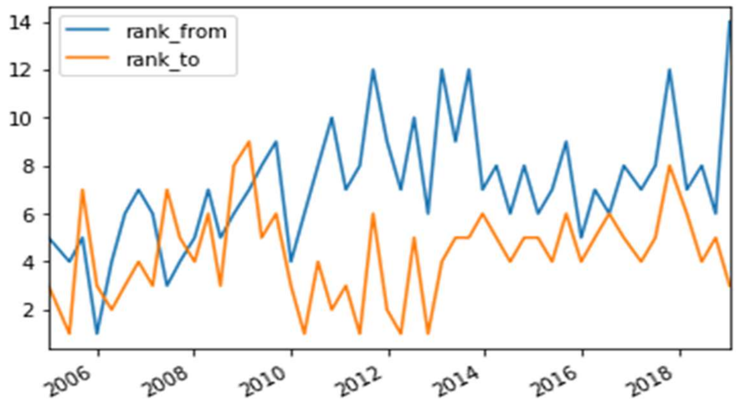
**Figure 10:** PC centrality ranking versus assets centrality ranking



4.3.2. Behavioral Changes of Banks in Response to Shocks

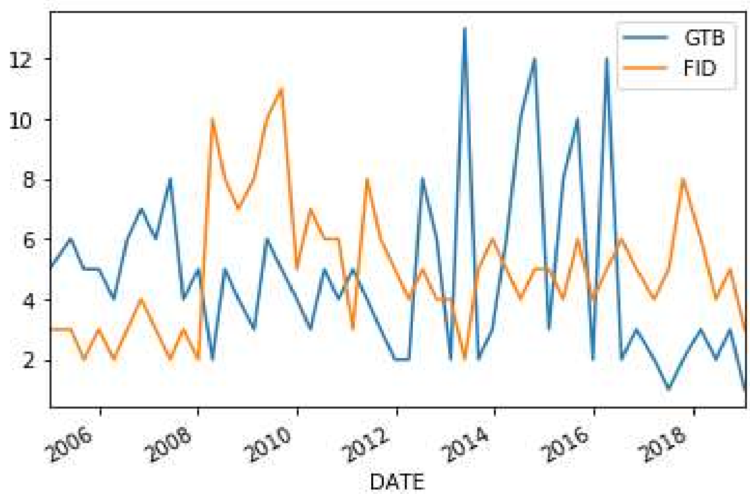
Banks respond differently to shocks in the network. Banks' response to shocks reveals their network roles as either shock transmitters or receivers. Figure 11 shows the evolution of the ZEN bank's PC centrality ranking as a borrower and a lender, respectively. ZEN Bank is a transmitter (lender) and a receiver (borrower) at the start of the network until 2010; afterward, it changes its role. For example, after 2010, ZEN bank began to have higher rankings of "to" centrality and lower rankings of "from." Afterward, ZEN bank played a little relevant role in the network as a receiver (borrower) but maintained its position as a transmit (lender). ZEN bank is more central as a contributor after a systemic event.

**Figure 11:** Changes in centrality behavior for ZEN bank.




Lastly, the network also provides some evidence of the change in behavior between the two banks based on the PC centrality rankings. A comparison of the centrality between bank GTB and bank FID in Figure 12, shows that bank GTB becomes more central during the two significant shocks (2000–2010 and 2017-2018). While, FID is more central in tranquil times. This evidence further emphasizes that banks' behavior varies and, to be precise, such variations are apparent after a systemic event. This implies that the relevance of each institution changes in terms of the PC centrality depending on the market condition.

**Figure 12:** Changes in centrality for two different banks.




These findings are elaborate as interconnectedness and systemic risk have not been examined with this frequency and from this viewpoint in the Nigerian banking system.

### *4.4. Robustness Check for Connectedness in the Nigerian Banking System*

This study adopts the EGARCH model to confirm the presence of shock volatility in the system. For clarity, simplicity, and economize on notations, the percentage change of the daily banking index (banking index return) was used as a proxy of all the banks in the system. Since the daily banking index in the stock market reflects the summary of bank stock movements in the stock market.

**Table 2:** The EGARCH model results

| Variable | Coefficient | p-values |
|---|---|---|
| $\mu$ | 0.045 * (0.012) | 0.000 |
| $AR_1$ | 0.154* (0.018) | 0.000 |
| $\omega$ | -0.040** (0.014) | 0.003 |
| $\alpha$ | 0.056** (0.020) | 0.050 |
| $\beta$ | 0.891* (0.025) | 0.000 |
| $\gamma$ | -0.043*** (0.054) | 0.073 |
| Q | 3.158 | 0.393 |
| $Q^2$ | 8.208 | 0.1174 |
| ARCH-LM | 5.092 | 0.2154 |
| Log-likelihood | -4027.49 | |

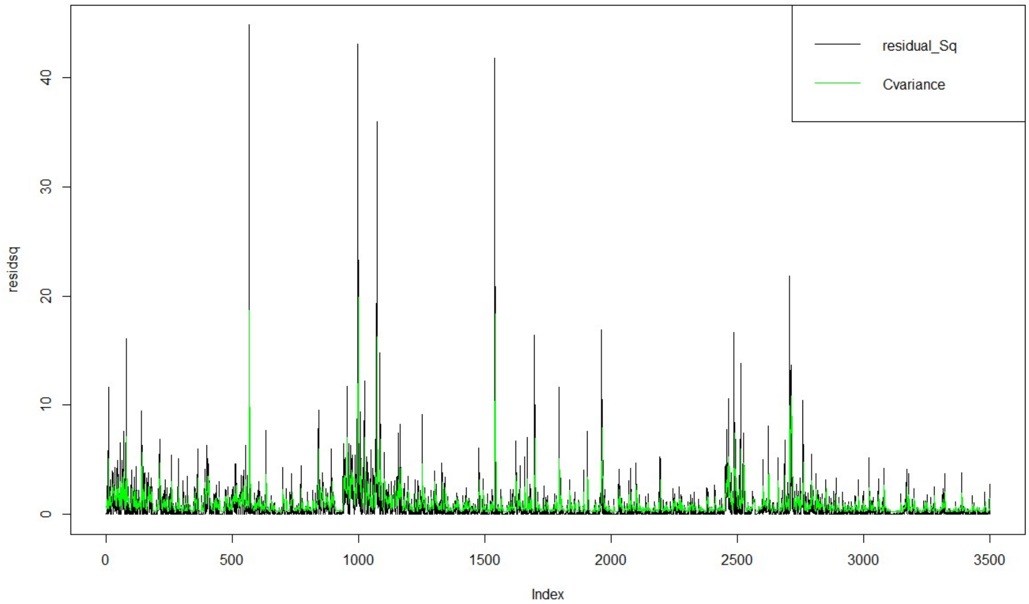
*Source:* Researcher's computation. Values marked as *, **, and *** indicate a significant level of 1%, 5%, and 10%, respectively.

Table 2 reports the outcome of the EGARCH model. The coefficients are reported concurrently with their standard errors in the brackets. Notably, the mean and variance equation coefficients are all significant. It implies that innovations (leverage effects) exist in the Nigerian banking system. The sum of the ARCH and GARCH terms ($\alpha+\beta$) is less than unity, implying persistent shock in the system. Its closeness to unity means the shock will persist for a long time before slowly converging to a steady state. $\alpha < \beta$ indicates that the GARCH effect is stronger than the ARCH effect. Also, the leverage variable ($\gamma$) coefficient is significant and negative. It implies that lousy news has more substantial effects than good news in the Nigerian banking sector. To check the robustness of the model Ljung-Box test was conducted on the residuals and residuals squared, as well as the ARCH-LM test. The estimates of the ARCH-LM test and the Ljung-box tests have all p-values more significant than 5%, suggesting that the model is free from heteroscedasticity and serial correlation in its residuals. The negative value of the leverage variable ($\gamma$) indicates that shocks are asymmetric, with the system responding to bad news more than good news.

Figure 13 plots the squared residuals and the estimated conditional variance from the EGARCH model. The black line is the graph of the squared residuals, while the green line is the graph of the conditional variance from the model. Figure 13 graphically shows the volatility in the model as indicated by the clustering pattern in both lines throughout the sample. The peaks signify periods of high volatility due to unexpected events (shocks) in the system. Volatility tracks investors' fears and periods of high volatility lead to high connectedness (shocks) resulting from fears expressed by market participants as they trade (Diebold & Yilmaz, 2014). This study analyses the pattern of volatility connectedness is of particular interest because we are particularly interested in crises, and volatility is particularly crisis-sensitive. For example, the peak around observation 600 coincides with the period around 2006 when the system witnessed new banks coming in. The cluster around observation 1000 is during the 2009 Nigerian banking crisis, and around observation 2500 downwards coincides with the 2016 recession, which was attributed to the fall in global crude oil prices in 2015.

The volatility graph from the EGARCH model shows that the system displayed intense instability throughout the study period. It confirms the time-varying connectedness results from the GFEVD model, which showed that spillover effects are higher during financial crunches or when the system is distressed. Hence, the EGARCH model's outcome agrees with the GFEVD model's result, and both models show that the Nigerian banking system is unstable (volatile) and displays the presence of persistent shocks.

**Figure 13:** The squared residual and the estimated conditional variance.




## 5. Conclusion

In this paper, we employ several network measures to estimate the connectedness of the Nigerian banking system and its implication for systemic risk assessment via banks stock returns. Using the generalized forecast error variance, we first obtain both the static and dynamic networks of the banks studied. From the estimated network, we capture the static and the time-varying characteristics of each bank's connectedness. Our results show that the system becomes less connected in tranquil periods and more connected in turbulent times; the system is unstable over time in response to shock. In addition, we consider six centrality measures for the robustness of our results and estimate a harmonized composite centrality metric using the PCA. The rankings of the composite centrality metric for each bank reveal the banks' systemic relevance. Accordingly, a bank with a more significant composite centrality metric is more relevant. We also analyzed the correlation between a bank's asset and systemic relevance. The finding shows a high association between an asset and the systemic relevance metric of the network, which further implies that banks with significant assets are more influential. The composite measure of systemic importance can be incorporated into the stress testing mechanisms to fast-track potentially risky banks. Finally, based on all the measures employed, the sampled banks have a substantial magnitude of overall connectedness. This makes it easier for a bank to spread its shocks to other banks in the system.

Measuring and evaluating Nigeria's banking system's connectedness have crucial policy implications. It will assist the CBN in systemic risk analysis and management and in formulating policies to manage future crises in the banking system. It has been observed that most policies pursued to address banking crises in Nigeria usually come when the crises have already crystallized. An evidence-based knowledge of the impact of the 2016 economic recession on the connectedness of the Nigerian Banking system will help the CBN to design an appropriate regulatory framework that will serve as a basis for responding to such crises in the future. This study adopts the financial network theory in assessing the behaviors and dynamics of banking interactions. The findings provide information about banks' connectedness and systemic importance from a macroprudential perspective. Therefore, it could provide valuable insights to regulators and policy-makers in understanding banks' behavior under certain conditions and aid investors in deciding portfolio choices and diversification. Since systemic risk emanates from connectedness, frequent assessment of the banking system's connectedness and systemic importance will aid policy decisions in monitoring possible channels through which shocks can quickly spread in the system so that preventive precautions can be made. The proposed measure of systemic importance can be incorporated into the CBN's stress testing mechanism for fast-tracking risk potential banks. Secondly, examining the dynamic connectedness shows that the system is frequently volatile. To instill stability in this system, it needs to be supported and make the business environment favorable. The evolution of the banking system revealed that after 2007, the system seemed to be static in terms of new entrants. There is a need to encourage new banks into the system. Regulations that would encourage new entrants should be put in place amid the implementation of the Basel Accord agreements. There is a need to improve the quality of stocks to make them more liquid. This will go a long way to build investors' confidence and stimulate the business environment.

However, to draw far-reaching conclusions concerning contagion dynamics and the banking sector's stability, more risk factors, such as other income sources, operational factors, and perhaps even behavioral features about the banking institutions, need to be incorporated. Future studies can consider the impact of such risk factors on systemic relevance as a possible extension of this study.

**Funding:** This research received no external funding.

**Conflict of Interest:** The authors declare that no potential conflict of interest was reported.

**Data Availability:** Data will be made available upon request.

**Author Contribution:** All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication. However, individual contributions are as follows: M-KJR: data curation, resource, methodology investigation, formal analysis, and writing the original draft. JSR: collected the dataset, formal analysis, review, and editing.

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