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BANK LENDING AND SYSTEMIC RISK: A BANKING-REAL SECTOR NETWORK CONNECTEDNESS APPROACH

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ABSTRACT: *This study examined the connectedness between the banking sector and real sector in Nigeria using a network analysis approach. It sought to seek if the shock from the real sector can be transferred to the banking sector in the context of systemic risk analysis. The findings reveals that base on the bank credit transfer from the banking sector to other sectors, the bank-real sectors are closely connected. Consequent of this, shocks from the real sector can spillover to the banking sector and vice versa. The results also, shows that the transport sector is the net transmitter of shocks while, the construction sector is the net recipient of shocks. They dynamic connectedness analysis showed that over the period of study bank-real sector connectedness varies with time and in response to economic phenomena. The study recommends that systemic risk surveillance should not be limited to the financial sector alone. Again, development policies should explore other sectors too rather than banking solely on the traditional agriculture-manufacturing sector development policy.*

KEY WORDS: Bank lending, systemic risk, network, connectedness, real sector

INTRODUCTION

Modeling the connectivity between the real and the banking sector and furnishing facts on how the interlinkages of bank lending is important for systemic risk surveillance and ensuring economic stability. The banking sector is most important financial intermediary in most developing economies and it is highly sensitive to shocks within the finance industry and the economy at large. The connectedness of the banking sector to other sectors can be through a network of various forms of exposures, either directly or indirectly. Through these connectivity, distress or shock can cause large losses unexpectedly on the banking system trades and economy. This can largely affect the financial condition of its counter parties. Substantial negative externalities or spillovers can be transmitted to the real economy, this is the core of systemic risk (Caruana, 2010 and Markose et al., 2012). The recent global financial crisis is an example of systemic risk of a global nature. In many developing countries like Nigeria, the primary effects of the crisis (the first round effect) was not experienced by it, due to the fact that Nigeria was not a key participant in the global economy. However, as the recession (consequent of the crisis) in advanced countries increased, the entire Nigerian economy was affected by its consequences. In specific terms, Nigeria was knocked by the crisis via both the financial and real media. The Nigerian economy is highly

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dependent on exports of crude oil and low export of other commodities as well as foreign capital inflows worsened the consequences of the foreign shock resulting from the crisis (Sanusi, 2012).

Nigeria witnessed a fall in demand for its oil export because of the downturn in the economies of her main trading associates. This, joined with the fall in the global price of oil, led to sharp reduction in foreign exchange income and thus, government revenue declined. The global financial crisis had negative effects on both the oil & gas sector and the capital market where the Nigerian banks were exposed to the tune of N1.6 trillion as at December 2008 (Sanusi, 2012). The outcome was a severe decline in the quality of banks' assets which prompted the concerns over banks' liquidity. Consequently, the Nigerian banking sector was immersed into severe crisis and many of the banks became distressed. As the crisis shocked the Nigerian banking sector, the central bank of Nigeria injected six hundred billion naira to rescue the banking sector (Olawale, 2015).

Recently, the global fall in crude oil prices which began in late 2015 threw Nigeria into another recession and foreign exchange crisis. Nigeria slipped into recession in the second quarter of 2016 and even recorded negative growth rate of real gross domestic product (GDP) was recorded for five consecutive quarters as published data by the National Bureau of Statistics (NBS) (Kazeem, 2017). The economy experienced a downturn which lasted for a year and until date the economy has not recorded any significant growth of up to 3% (NBS, 2019). The Nigerian government had used up its reserves from the boom in the oil prices in the previous years. The decline in the international price of oil, this threw the Nigerian economy into recession again and extreme decline in foreign exchange receipts. The country relies mainly on oil revenue to generate funds for running the economy and highly dependent on importation for both consumer goods and inputs. Low foreign reserves due to poor accumulation of forex was also a contributing factor leading to the drastic depreciation of naira. The financial crunch resulting from the recession was intense in the banking sector. Many banks had exposure to the oil sector and power - with the fall in the oil price - huge investments were lost and an incidence of high non-performing loans emerged in the banking sector. Owing to the financial crunch, many bankers were laid off and branches shut down. Two banks were worst hit by the crisis: Diamond bank which later was acquired and Skye bank was sold out by the asset management company of Nigeria. The crisis generated panic about the stability of the entire financial system as it was feared that history was about to repeat itself.

Billio et al. (2012) asserted that systemic risk arises from a group of institutions that are interrelated by common profitable business associations which can become the medium of spreading illiquidity, insolvency, and losses during periods of financial turbulence throughout the financial system. Diebold and Yilmaz (2014) stressed that connectedness is key to contemporary risk quantification and management. It mainly features in diverse areas of connectedness that risk is capable of emanating from. It is also core to comprehending the essential macroeconomic risks, particularly trade cycle risk (intra- and inter-country real activity connectedness). Zigrand (2014) defined systemic risk as the risk to the actual working of the system as well as the risk produced by the system. That is, the possibility that an event from an institution could trigger intense instability or breakdown an entire system. It is important to measure systemic risk to enhance better decision making and risk management, because it involves the risk emanating from the shock to one or more financial institutions which transmits such negative effects to other institutions on the system and economy in general.

The problem of including the real economy in systemic risk analysis emerges primarily due to (a) the limited access to tiny bilateral linkages on bank loans to the real sector and to the interbank market and/or (b) the limited systemic risk models that catches the feedback reaction between the real and banking sectors in the literature. The reactive response between these two sectors actually show how the bank-real sector relationship as economic fundamentals are capable of magnifying shocks. Shocks can begin in the real sector and crossover to the banking sector, which in return can exacerbate these shocks first and foremost, thus giving rise to a domino effect by worsening farther the financial wellbeing of the real sector and so forth (Silva, 2017). This push and pull mechanism can only be examined by including the interaction between banks and real sector.

The study is motivated by the fact that shocks from the real sector can have feedback repercussions for the banking sector and vice versa, which in extreme situation can lead to systemic risk. The Nigerian banking sector has suffered shocks from the real sector as seen the two cases discussed above. How connected is the Nigerian banking sector to other sectors of the economy? Which of the other sectors of the economy are more connected to the banking sector in Nigeria? This study intends to broaden the understanding of the connectedness between the banking sector and other sectors of the Nigerian economy. This study is crucial for policy decision in this period of economic diversification in Nigeria and maintenance of banking sector stability in mitigating for systemic risk.

Subsequently the study is organized as follows: Section two contains literature review, Section three bears the methodology and data, Section four is the empirical analysis and discussion, while, Section five contains conclusion and policy recommendations.

LITERATURE REVIEW

The literature survey will focus on studies related to the current study. The empirical literature on the usage of network theory in economic analysis is fairly wide, especially in comprehending intricate macro-economic interdependencies. For instance, Silva et al. (2017), analyzed feedback effect of the financial and real sector network on systemic risk, using Brazilian supervisory and accounting data of banks and firms. Their evidence reveled a significant network reaction in which the network properties can either reduce or magnify shocks from the real sector and thus plays a significant role in transmission processes. They developed a model based on (Battiston et al., 2012) and differential (Bardoscia et al., 2015) DebtRank formulations. Again, some literatures focus on connectedness and systemic risk within the banking sector such as, Peltone, et al. (2018) used the macro-network to evaluate the interlinkages of the banking sector and connected it to banking crises in Europe. They found that a more key position of the banking sector in the macro-network substantially increases the chances of a banking crisis. Their evidence from the analysis of various sources of risk revealed that credit is a relevant medium of fragility. They also showed that early-warning models combined with connectedness measures surpassed conventional models in terms of out-of-sample prognosis. Petrone and Latora (2018) illustrated how interrelationship of financial institutions affects soundness and credit crunches among banks. They quantified system risk by introducing a probability default model, a dynamic model that joins credit risk measures with a contagion processes on the network of expositions among banks. They illustrated how the model works on the web of the European global systemically important banks. Their findings revealed a substantial transmission regime where lower default association between banks led to higher losses. This is contrary to the diversification gains anchored by traditional credit risk models used by banks and supervisory bodies who could therefore undervalue the capital required to surmount a period of distress, thus enhancing financial system instability. Hale and Lopez (2019) proposed a method for assessing connectedness in US banks using information at firm level. Their results showed how mixed-frequency models can be used to decomposed bank outcome variables in network analysis to measure connectedness across firms. Roukny, et al. (2018) introduced a model to quantify the single and general probability of non-payment in a system of banks linked in an overall network of credit contracts and susceptable to external shocks with a common correlation property. They showed the repercussion of instability on the computation of systemic risk in terms of anticipated losses. Leur, et al. (2017) investigated the factual content of quantifiers for systemic risk ratings based stock association network. Using European banking data, they showed that correlation based network measures can be used as a supplement to the available methods of systemic risk classification depending on book or market values.

Some studies on connectedness and systemic risk analysis which are not country specific includes: Demirer, et al., (2017) employed the LASSO methods to reduce, choose, and analyze the large-dimensional network connecting the publicly traded subgroup of the world's biggest 150 banks. Bongini, et al. (2018) showed how interlinkages in the worldwide banking network lowered due to the global financial crisis and consequent supervisory moves were fruitful in inducing the globally systemically relevant banks to contain their systemic structure. Constantin et al. (2018) presented network relatioships into an early-warning model to dictate distress among European banks. They employed the multivariate extreme value theory to measure equity-based tail-connected networks. Their findings revealed that early warning models incorporating computed tail dependencies are concordantly better than bank-specific standard models without networks. Their results also suggested that the presence of interdependence in early-warning models, and moves toward an integrated depiction of cyclical and cross-sectional dimensions of systemic risk. Some other studies focuses on connectedness and systemic risk among macroeconomic fundamentals. For example, Ahmad, et al. (2018) examined the financial interrelationship of Brazil, Russia, India, China and South Africa (BRICS) and global sovereign bond markets founded on variance decomposition. They found that Russia and South Africa are net transmitter of shocks within the BRICS. China and India exhibits low dependence indicating that they may be a helpful cover against loss and diversification of potentials. Ogbuabor, et al. (2016) examined the real and financial dependence of some African economies with the universal economy using VECM. Their findings revealed that US, EU and Canada subjugate Africa’s equity markets, while China, India and Japan surmount Africa’s real activities. Their findings suggests that African economies prove to be small open economies, systematically unimportant and susceptible to shocks from subjugating global economies.

The recent global financial crunch that was widely spread reemphasizes the extensive search for various sources of shocks to the financial sector via its complex web of exposures. Previous studies on financial-real sector dependence in Nigeria was not country specific. This study contributes to literature by widening the understanding of real-banking sector connectedness and systemic risk in the Nigerian banking sector. By narrowing the study to the study to the real-bank sector dependence and also using different variables from previous related study on Nigeria sectoral dependence.

METHODOLOGY AND DATA

Diebold and Yilmaz in their series of papers 2012 and 2014, developed a network approach measures of connectedness founded on the generalized forecast error variance decomposition (GFEVD) by employing the "generalized identification" architecture of Koop, et al. (1996) and Pesaran and Shin (1980), which creates variance decompositions unchanging to ordering. This connectedness approach rested on examining shares of forecast error variation in of different firms or fundamentals due to shocks arising elsewhere. Intuitively variance decompositions as measure of connectedness are attractive because they allow at the most granular pairwise level, the assessment of "How much of entity i's future uncertainty (at horizon H) is due to shocks arising not with entity i, but rather with entity j?" This means that the measures allow for the examination of shocks to an institutions or economic fundamental consequent of shocks arising from other institutions or economic fundamentals. Here the focus is on the non-own shock of an institution or fundamentals. The network connectedness measures of Diebold and Yilmaz, can be able to show the direction and strength of linkages among entities or fundamentals in the system and be used to study the dynamic dependence among entities in complex systems.

3.1 Network connectedness measures

Firm j's share of firm i's H-step-ahead generalized forecast error variance, $V_{ij}^{g}(H)$, is

$$V_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \sum e_j\right)^2}{\sum_0^{H-1}(e_i' A_h \sum A_h' \, e_i)}, \quad H = 1,2,3,\dots, \tag{1}$$

Where Σ is the covariance matrix of the disturbance vector ε, σ_{jj} is the standard deviation of the disturbance of the jth equation, and e_i is the choosing vector with one as the ith component and zeros otherwise. In the Koop et al generalized VAR environment, the variance contributions do not necessarily add to 1; that is, in general $\sum_{j=1}^{N} V_{ij}^{g}(H) \neq 1$. Since shocks are not mandatorily orthogonal in the generalized variance decomposition GVD framework, total of shares forecast error variance are not inevitably unity. Thus we normalize each input of the generalized variance decomposition matrix (Equation 1) by totaling the row to get pairwise directional interaction from firm j to firm i:

$$\tilde{V}_{ij}^{g}(H) = \frac{V_{ij}^{g}(H)}{\sum_{j=1}^{N} V_{ij}^{g}(H)} \tag{2}$$

Now by construction $\sum_{j=1}^{N} \tilde{V}_{ij}^{g}(H) = 1$ and $\sum_{ij=1}^{N} \tilde{V}_{ij}^{g}(H) = N$.

To reduce symbols, we now transform from $\tilde{V}_{ij}^{g}(H)$ to $C_{i\leftarrow j}^{H}$ (C is proxy for connectedness), which is less bulky and simple.

Total directional dependence to firm i from all other firms j is

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$$C_{i\leftarrow\bullet}^{H} = \frac{\sum_{j=1}^{N} \tilde{V}_{ij}^{g}(H)}{\sum_{ij=1}^{N} \tilde{V}_{ij}^{g}(H)} = \frac{\sum_{j=1}^{N} \tilde{V}_{ij}^{g}(H)}{N} \tag{3}$$

Consequentially, total directional connectedness from firm i to all other firms j is

$$C_{\bullet\leftarrow i}^{H} = \frac{\sum_{j=1}^{N} \tilde{V}_{ij}^{g}(H)}{\sum_{ij=1}^{N} \tilde{V}_{ij}^{g}(H)} = \frac{\sum_{j=1}^{N} \tilde{V}_{ij}^{g}(H)}{N} \tag{4}$$

Lastly, the system-wide connectedness measure is derived, using the normalized inputs of the GVD matrix (Equation 2), we measure total directional connectedness as

$$C^{H} = \frac{\sum_{ij=1}^{N} \tilde{V}_{ij}^{g}(H)}{\sum_{ij=1}^{N} \tilde{V}_{ij}^{g}(H)} = \frac{\sum_{ij=1}^{N} \tilde{V}_{ij}^{g}(H)}{N} \tag{5}$$

This is called the total connectedness or system-wide connectedness. It is the sum of total directional dependence either "to" or "from." (Whichever way, "exports" must equal "imports" at the "international" level).

3.2 Data

Following Silva et al. (2017), this study uses the monthly sectoral bank loans and the loan-to-deposit ratio from the central bank of Nigeria (CBN), to examine the bank-real sector relationship in the Nigerian economy. The choice of data is due to its frequent, availability and accessibility rather than daily balance sheet which is not readily available. The study period spans from January 2014 to June 2019. The sectoral loans are the proxy for the real sector while, the loan-to-deposit ratio is the proxy for the banking sector. The loans are measured in naira (Nigerian currency), the log of the loans are taken as a way of standardization and bringing it to the same base with the banking sector measure which is in ratio. The list of sectors and acronyms are:

Agriculture: AGR, solid mining and querying: SMQ, manufacturing: MFR, oil & gas: OIL, power and energy: ENP, Construction: CON, trade/general commerce: TDE, real estate: REA, information & communication: INC, transportation & storage: TRN, government: GOV, loan-to-deposit ratio LDR.

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Table 1: Descriptive statistics

	AGR	SMQ	MFR	OIL	ENP	CON	TDE	REA	INC	TRN	GOV	LDR
Mean	540482.91	18340.87	2125223.2	4305703.8	661293.78	618789.2	1028449.2	683968.1	797111.01	378585.2	1228269.8	69.42
Max	772375.4	222302.5	2650673.3	5006846.3	789413.46	723147.6	1262913.9	804269.2	984315.02	503476.38	1539224.7	82.77
Min	446912.33	6156.52	1649852.5	3023021.5	393529.9	467751.6	907846.3	541054.9	545498.2	289852.02	584508.02	57.37
Std. Dev	78330.48	27446.7	224433.9	64384863	108746.53	51396.97	80450.44	86447.26	92858.7	62206.5	273419.88	7.71
Skewness	1.0906	0.0007	0.2928	-0.9153	-0.7605	-0.6386	1.1059	-0.0466	-0.7953	0.0729	-1.3015	0.23
Kurtosis	0.4181	54.07	0.1006	-0.9813	-0.8155	1.0038	1.3207	-1.5986	0.9676	-1.3191	0.0508	-1.23
Observ.	72	72	72	72	72	72	72	72	72	72	72	72

Source: Researchers' computation

Table 1 reports the results of the descriptive statistics of the series. The coefficients of skewness indicates a moderately symmetrical distribution for all series. The coefficient of kurtosis for all series is less than three except for SMQ, it implies the series have a flat probability distribution the indicating the absence of outliers. It implies that the series are platykurtic the assumption of normality is thus rejected. The mean, maximum and minimum values shows that the oil & gas (OIL) sector has the highest values, followed by government (GOV) and trade (TDE) sectors. This further reveals the large dependence on crude oil and importation as such majority credits is given to such sectors starving other sectors that can spur endogenous growth funds.

4. Empirical analysis and discussion

4.1 Correlation analysis

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Table 2: Correlation analysis

	AGR	SMQ	MFR	OIL	ENP	CON	TDE	REA	INC	TDR	GOV	LDR
AGR	1											
SMQ	-0.1819	1										
MFR	0.8352	-0.1648	1									
OIL	0.486576	-0.2013	0.7034	1								
ENP	0.3199	-0.2335	0.5754	0.9500	1							
CON	0.5983	-0.0642	0.8018	0.6476	0.5420	1						
TDE	0.4262	0.3646	0.2588	-0.063	-0.1920	0.33445	1					
REA	0.8220	-0.1802	0.7931	0.6938	0.5726	0.6951	0.2943	1				
INC	0.2528	-0.0518	0.1448	0.6425	0.7602	0.1896	-0.4197	0.0412	1			
TDR	-0.3952	0.0099	-0.1312	-0.0521	-0.0075	0.0256	-0.1345	-0.3689	0.3639	1		
GOV	-0.5000	0.2304	-0.2913	-0.2479	-0.2209	-0.2324	-0.1970	-0.6031	0.1875	0.6208	1	
LDR	-0.4874	0.027	-0.0473	0.1774	0.3039	-0.0249	-0.5063	-0.3741	0.6966	0.5345	0.6815	1

Source: Researchers' computation

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We start with the discussion of the unconditional correlation analysis as reported in table 2. While most of the series exhibit low association. The oil and power sectors (OIL and ENP) are highly correlated with a value of 0.95%. This is because the sectors tend to attract high loans due to the limited diversification of the economy. The Nigerian economy relies mostly on the oil sector as its major source of revenue, the power and energy sector is an emerging sector as such both sectors are closely linked. This results further supports the assertions that most banks have high non-performing linked to these oil and power sectors. With the fall in the global crude oil price loans were not able to be repaid, as seen in the case of Diamond bank which was later acquired. The agriculture (AGR) and manufacturing (MFR) sectors also have high correlation, this is due to the fact that they are both preferred sectors that are intended to promote development according to government policy.

NETWORK CONNECTEDNESS ANALYSIS AND DISCUSSION

Here we discuss the connectedness measures proposed in Diebold and Yilmaz 2012 and 2014, which is the GFEVD for the static network analysis and a rolling window analysis for dynamic network analysis. Table 3 gives the results of the static and unconditional analysis. It describes the shocks or connectedness arising from the share of the forecast error variances of each of the sectors. That is, the calculated share of the forecast variance error of i attributed to shocks to variable j known as the pairwise directional dependence. The diagonal component are the own-connectedness. The column labelled, “From”, shows the total connectedness or spillovers received by a specific sector from all other sectors whereas the row labelled “To” shows the spillover effect contributed by a particular sector to all other sectors. The bottom right corner, “Total” indicates the level of total interaction or system wide interrelationship that is the overall connectedness in the system. The row with name “Net” indicates the net pairwise directional interaction, the difference between the contribution “To” other sectors and contribution “From” other sectors. A negative value indicates a net receiver and a positive value indicates a net giver.

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Table 3: Connectedness table (static and unconditional network analysis)

	AGR	SMQ	MFR	OIL	ENP	CON	TDE	REA	INC	TRN	GOV	LDR	**FROM**
AGR	0	1.12	1.91	1.96	1.96	1.74	1.88	1.85	1.88	1.94	1.94	0.86	19.04
SMQ	0.62	0	0.72	0.8	0.78	0.95	0.86	0.87	0.82	0.77	0.85	0.1	8.14
MFR	1.67	0.92	0	1.7	1.71	1.48	1.64	1.57	1.59	1.7	1.66	0.84	16.48
OIL	4.8.4	2.79	4.94	0	5.06	4.69	4.9	4.89	4.88	5.02	5.03	1.98	49.02
ENP	4.54	2.65	4.6	4.71	0	4.3	4.53	4.47	4.5	4.64	4.67	1.98	45.59
CON	12.77	9.37	13.34	14.43	14.47	0	14.01	14.86	14.27	14.12	15.08	3.35	140.07
TDE	2.2	1.22	2.27	2.35	2.35	2.18	0	2.29	2.3	2.29	2.35	.94	22.74
REA	1.78	0.97	1.78	1.9	1.87	0.18	1.87	0	1.91	1.83	1.9	0.69	18.3
INC	10.08	5.4	9.86	10.54	10.36	9.87	10.39	10.57	0	10.21	10.55	3.57	101.58
TRN	1.57	0.99	1.54	1.58	1.59	1.41	1.48	1.48	1.51	0	1.57	0.69	15.41
GOV	2.98	1.9	2.95	3.12	3.11	2.98	3.03	3.06	3.07	3.05	0	1.04	30.29
LDR	0.84	0.44	0.94	0.97	0.98	0.95	0.99	0.95	0.92	0.96	0.97	0	9.91
TO	43.91	27.76	44.86	44.06	44.24	32.35	45.57	47.05	37.68	46.53	46.57	16.03	476.57
NET	24.87	19.62	28.38	-4.96	-1.35	-107.72	22.83	28.75	-63.95	31.12	16.28	6.12	**39.71%**

Source: Researchers' computation

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The system-wide connectedness is 39.71% which implies that there is an average overall connectedness in the system. Even though the overall connectedness of the series is moderate, that does not imply that the shock from the real sector to the banking will be moderate. A total connectedness value of 39.71% between the real and banking sector is high from the decision making perspective. Meaning that the real sector performance have high implication on the banking system. This explains the reason for the distress in the banking sector whenever the real sector is experiencing a downturn especially the oil & gas sector. The oil & gas sector has a close connectivity with the banking sector and is tightly linked to other sectors that are strongly linked to the banking sector like CON and INC, this makes it easier for the diffusion of shocks in the system. The findings are similar to Silva, et al. (2017) and Ahmad et al. (2018).

4.3 Dynamic connectedness analysis

Here, the focus will be on the time-varying connectedness by employing the rolling estimation analysis on a six months rolling window width. The dynamic analysis enables us to identify the impact of major economic events on connectedness.

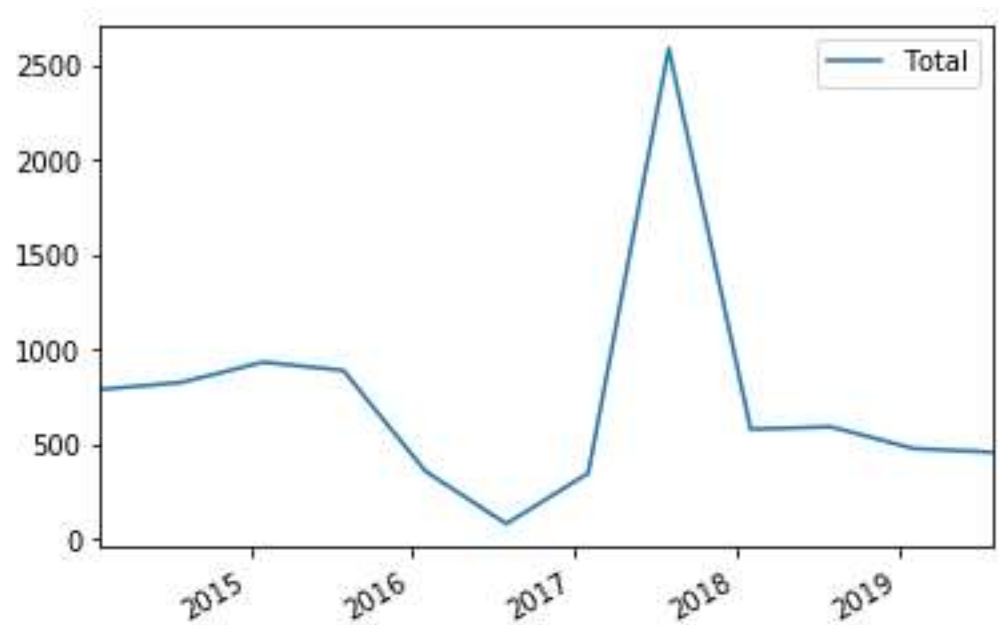

Figure 1. System-wide connectedness

Figure 1 is the plot of the rolling sample point plot of the overall connectedness for the sectoral bank credits and the loan-to-deposit ratio in the Nigerian banking sector. It is noticeable that towards the end of 2015 to 2017 a large trough exist which coincides with the period of recent fall in global crude oil price and recession in the Nigerian economy. This implies that around this period the banks restricted the giving of credit as economic activities were generally low and leading to the financial crunch. Around 2018 the peak indicates the recovery period and increased connectedness and later decrease as the economy is still striving to recover fully. The dynamic total and net directional connectedness also exhibited a similar feature as described above, there is

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no need of plotting them to avoid vain repetition. The results are analogous to Ogbuabor et al. (2016).

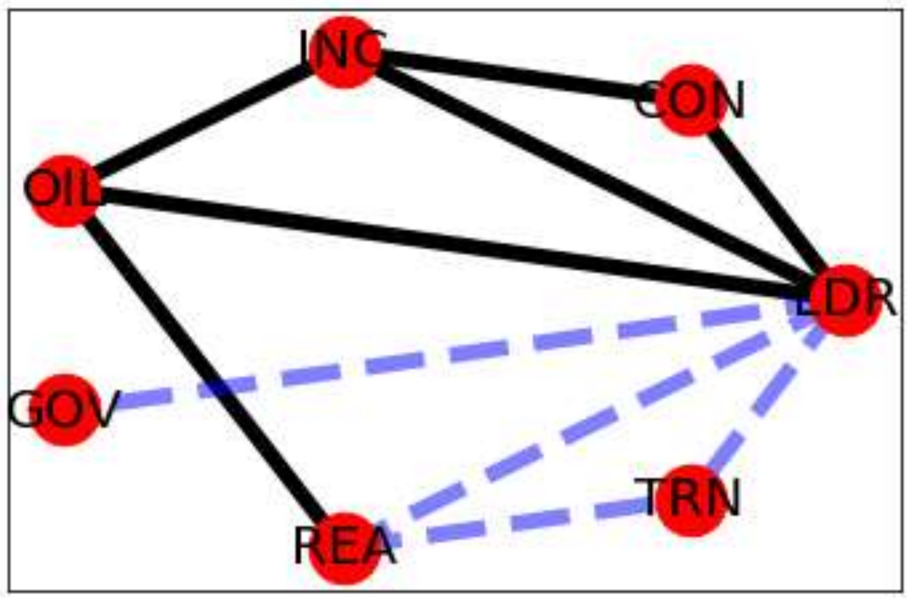

Figure 2. Network graph

Figure 2 summarizes the network of connectedness. It is a weighted network graph showing the strength of connectedness among some selected sectors. The sectors with strong bi-directional strength of relationship are linked with the thick black line. Similarly, the dash blue arrows refers to weak strength of relationship. For example, LDR, INC, CON, OIL and ENP have all bi-directional strong pairwise connectivity. While, LDR, REA, GOV and TRN have weak bi-directional pairwise relationship. On the other hand, REA is strongly connected to OIL and weakly connected to TRN. This implies the presence of high connectedness between the pairs of some nodes (sectors) and low connectivity of some nodes. The pattern of connectivity also reveals some sectors like INC and CON are tightly connected to all nodes in the network this makes them more central in the network. The network displays a scale-free property with few highly connected nodes and a low connectivity of most of the nodes.

CONCLUSION AND POLICY IMPLICATIONS

This study examined the connectedness between the real and banking sector, based on network connectedness measures rooted in variance decompositions developed by Diebold and Yilmaz (2014). The study was motivated by the fact that happenings in the real sector often times have devastating effect on the banking sector most especially the oil and gas sector. The findings of the study reveals a close relationship between the banking sector with the construction and information & communication sectors. Next in line to these in high connectivity to the banking sector is the oil & gas and power & energy sectors. While sectors nodes are highly connected, others are weakly connected such as the solid mining & querying. The time-varying connectedness analysis reveals the behavior of the system in response to shocks.

Revelations from the descriptive analysis shows that the oil and gas sector receives the highest bank credit from the banking sector which is seconded by the trade sector. The implication of this is that the banking sector aiding the promotion of oil dependency and high importation of goods and services. This brings to attention that financial surveillance of systemic risk analysis should be more diversified to include risks channels emanating from the real sector. Policy measures should be taken to stimulate other sectors if the desired economic diversification would become a reality. Evolving sectors such as construction and information & communication have strong connectedness with the banking sector and other sectors. Considering the advancement in technology going on all over the world, the information & communication sector should be promoted. The construction sector also reiterates the need for developing infrastructure and amenities to boost all other sectors of the economy. The study recommends a paradigm shift in Nigerian development strategy to include emerging sectors such as construction and information & Technology.

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