VOLATILITY TRANSMISSION AND CO-MOVEMENT BETWEEN NIGERIAN AND UNITED STATES OF AMERICAN BOND MARKETS

By

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ABSTRACT

The issue of co-movement and spillover among international bond markets is very important in asset allocation management and investors' diversification strategies. This paper examines the co-movement between the Nigerian and United States (US) bond markets by adapting a class of conditional correlation of the Multivariate Generalize Autoregressive Conditional Heteroscedasticity (MGARCH) framework, the Dynamic Conditional Correlation (DCC) model. The result of this study reveals a weak negative relationship between the Nigerian and US bond markets and concluded that the correlation will in time return to the long-run unconditional level, due to evidence of mean reverting. Finally, these findings are informative to both investors and policy makers working or investing in the Nigerian bond and capital markets. As a result, there is need to identify the specific factors that generate the co-movement in the bonds of the two markets.

INTRODUCTION

The capital markets which comprises of the stock and bond markets are two of widely followed markets by economists and researchers. Their daily movements have been consistently analyzed and closely followed as a result of their impact on a country's economic growth. In Nigeria, the financial instruments used in the capital market like other capital markets in the world include both stocks and bonds, as such, create interest from both investors and academicians.

Nigerian capital market has experienced considerable growth and development since 1970s, when the Nigeria's sovereign bonds came to existence. Though it was illiquid and redeemable only to the Central Bank of Nigeria (CBN) upon maturity, it has recently increase in bonds issuance from both State governments and private companies, with States like Lagos, Ogun, Rivers, Imo (issued 2016, 18.5b naira @ 15.5%), Bayelsa, and Abia States have either issued or received approval to issue bonds for long-term capital projects. More significantly, it has become more attractive to prestigious international issuers, because of the recent reforms carried out by the Security and Exchange Commission (SEC) in Nigerian domestic bond market (Oteh, 2013).

It is established that bond markets – bond yields and returns are positively correlated across countries (Hafer, Kutan, and Zhou, 1997) and influenced by market conditions of other countries (NSE, 2016) – indicating that international bond markets are linked together. Therefore, studies on volatility transmission across bond markets helps investors understand the behavior and source of cross-market volatility transmission (Cai, Jiang, and Kumar, 2004; Fleming, Kirby, and Ostdiek, 1998).

In spite of this and the immense potential of the Nigerian bond market, most of the literature on international co-movement across markets are focused on Nigerian stock market and government bond markets of developed economy (Steeley, 2006; Bunda, Alexopoulou, and Ferrando, 2009). Multivariate GARCH framework, has proven to be the very efficient in modeling markets transmission and co-movement (Emenike, 2014). Studies like Piljak (2013); Skintzi and Refenes (2006); Christiansen (2003), Steeley (2006); Lin, Wang, and Gau (2007) applied MGARCH models in modeling volatility transmission or co-movement among several bond markets.

This paper examines the dynamic relationships between the Nigerian and US bond markets. The study employs the DCC (1, 1) MGARCH model that allows time-varying conditional correlations while investigating the dynamic properties of two markets returns. It also provides some interesting findings that contribute to the understanding of the time-varying nature of volatility spillover effects between Nigerian and US bond returns. rkets transmission and co-movement

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METHODOLOGY

Research Design

The study adapted a qualitative research design and the data is collected through a secondary source, available on http://www.tradingeconomics.com. The data collected are weekly observations of the 10 year US and Nigerian Federal Government bond yield from December 14, 2007 to December 27, 2014, representing the returns from Nigerian stock and bond markets respectively. The study employs the Augmented Dickey Fuller (ADF) test statistics to confirm the stationarity of the process while the Jarque-Bera test to check the normality of the returns series. The bivariate MGARCH, the DCC approach is further used to measure the co-movement between the two bond returns. 1 to be the very efficient in **METHODOLOGY**

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2016): Christiansen (2003). Steeley (2006):

design and the data is collect

Computation of Return Series from Price

Compounded weekly return of each series of each index is generated as follows;

$$
r_{t} = 100 \times \ln\left(\frac{P_{t}}{P_{t-1}}\right) \tag{1}
$$

where r_t is the return for period t; $P_{_t}$ and $P_{_{t-1}}$ are \qquad returns in thi price index on week *^t* and *t-1* respectively, and *ln* is the natural logarithm. According to Christoffersen (2012),

Dynamic Conditional Correlation MGARCH (DCC-MGARCH)

The DCC model, proposed by Engle and Sheppard (2001) and Engle (2002), is a new class of multivariate model, which is particularly well suited to examine correlation dynamics among assets. The DCC approach has the flexibility of univariate GARCH but without the complexity of a general multivariate GARCH. As the parameters to be estimated in the correlation process are independent of the number of series to be Component weekly return the service of the multistic spin term is significant to the form of Eq. (1) have better station-

where r_i is the return for period t: P , and P_{i-1} are

properties.

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$$
r_t = \sim_t + V_t
$$

vector of the returns, *ε^t* is a (*k*×1) vector of zero mean

returns in the form of Eq. (1) have better statistical properties.

correlated, a large number of series can be considered in a single estimation.

Following Bollerslev (1990), Engle and Sheppard (2001) and Engle (2002), we start our empirical specification with the assumption that US and Nigeria bond returns are multivariate normally distributed with zero mean and conditional variance-covariance matrix *H^t* . Our multivariate DCC-GARCH model can be **Example the transies from Price**
 $r_i = 100 \times \ln(\frac{P_i}{P_{i-1}})$ (1)
 $r_i = 100 \times \ln(\frac{P_i}{P_{i-1}})$

is the return for period t: P_i and P_{i-1} are
 $r_i = 100 \times \ln(\frac{P_i}{P_{i-1}})$
 $t = 100 \times \ln(\frac{P_i}{P_{i-1}})$
 Conditional Correla

return innovations conditional on the information, Ω*t-*¹ available at time *t-*1 and the conditional variancecovariance matrix (*Ht*) in the DCC model can be expressed as:

Hermail of Science, Technology & Education (JOSTE); Vol. 5 (2), June, 2017
 H₁ = *D₁ R₁ D₁

represents a (* k \land *) diagonal matrix of the equation of each asset in

d volatility of the returns on each asset i* where *D^t* represents a (*k*×*k*) diagonal matrix of the conditional volatility of the returns on each asset in the sample and \mathcal{R}_t is the ($k \times \mathcal{R}$) conditional correlation matrix. The DCC-GARCH model estimates conditional volatilities and correlations in two steps. In the first step the mean 1 1 **Example 15 colence, Technology & Education (JOSTE); Vol. 5 (2), June, 2017**
 2 matrix (*H_i*) in the DCC model can be
 2 expressed as:
 2 $H_i = D_i R_i D_i$

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covariance matrix ($H_i = D_i R_i D_i$

where B_i represents a ($k \nmid A$) diagonal matrix of the equation of each asset in

conditional volatilit volatility of the returns on each asset in the
 R_i is the $(k \times k)$ conditional correlation matrix.

RCH model estimates conditional volatilities

tions in two steps. In the first step the mean
 $P_t = (h_{iii}^{1/2}, \dots, h_{kkt}^{1/2$ $(\mathcal{M}\otimes\mathcal{M})$ diagonal matrix of the

ne returns on each asset in the

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 R_t is the ($k \approx R$) conditional correlation matrix.

RCH model estimates conditional volatilities
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e** matrix (*H_i*) in the DCC model can be expressed as:
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 Covariance matrix (*k*) in the DCC model can be expressed as:
 $H_i = D_i R_i D_i$

where B_i represents a (*k-k*) diagonal matrix of the equa *D. kournated Science.* Technology & Education *DOSTEI:* You, S. (2), Ame. 2012

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Since metric (N_d) in the DCC mulel can be
 $H_i = D_i R_i D_i$
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constrained exh

$$
D_{\scriptscriptstyle t}=\left(h^{\not\! \gamma_2}_{i_{tt}} ,....h^{\not\gamma_2}_{k_{kt}} \right)
$$

where: *hiit*, conditional variance of each asset, is The DCC-GARCH model estimates conditional volatilities
and correlations in two steps. In the first step the mean
 $D_t = (h_{iit}^{\gamma_2}, ..., h_{kkt}^{\gamma_2})$
where: h_{iitk} conditional variance of each asset, is
assumed to follow a uni $D_i = (h_{iii}^{V_2}.....h_{kk}^{V_2})$

ere: h_{iii} conditional variance of each asset, is

sumed to follow a univariate GARCH (p_i, q_i) process,

en by the following expression:
 $h_{i,i+1} = w_i + \sum_{p=1}^{P_i} \Gamma_{i,p} V_{i,i+1-p}^2 + \sum_{q=1}^{q_i} S_{i,q$

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Covariance matrix (H_0) in the DCC model can be expressed as:	($H_1 = D_1 R_1 D_2$, (3)) where D_i represents a $(k \times A)$ diagonal matrix of the conditional volatility of the returns on each asset in the conditional volatility of the returns on each asset in the sampling and R_i is the $(k \times A)$ conditional correlation matrix.	estimated. Hence, we can define D_i as follows:
The DCC-GARCH model estimates conditional volatilities and correlations in two steps. In the first step the mean $D_i = (h_{i\alpha}^{(k)} \tldots h_{i\alpha}^{(k)})$ where: $h_{i\alpha}$ conditional variance of each asset. is assumed to follow a univariate BARCH (p_i, q_i) process.	(4)	
However, to ensure non-negativity and stationary some restrictions, such as:	(5)	
$H_{i,\alpha+1} = W_i + \sum_{p=1}^{p_i} \Gamma_{i,p} V_{i,\alpha+1-p}^2 + \sum_{q=1}^{q_i} S_{i,q} h_{i,l-q}$ where $I_{i,p} > 0$; $S_{i,q} > 0$ and $\sum_{p=1}^{p_i} \Gamma_{i,p} V_{i,\alpha+1-p}^2 + \sum_{q=1}^{q_i} S_{i,q} h_{i,l-q} < 1$ should be imposed. These univariate variance estimates are then used to standardize the zero mean return innavations for each asset. In the second stage, return measiduals are transformed by their estimated standard of the conceptual in the DCC model is given by		

$$
r_{i,p} > 0; \, s_{i,q} > 0 \text{ and } \sum_{p=1}^{p_1} r_{i,p} v_{i,t+1-p}^2 + \sum_{q=1}^{q_1} s_{i,q} h_{i,t-q} < 1
$$

should be imposed. These univariate variance estimates are then used to standardize the zero mean return innovations for each asset. In the second stage, return residuals are transformed by their estimated standard deviations from the first stage. That is BARCH model estimates conditional volatilities

taking in two steps. In the first step the mean
 $D_i = (h_{ci}^{(j)}, \ldots, h_{io}^{(j)})$

(a) conditional variance of each asset, is

to conditional variance of each asset, is

to find t 2 is the *C* $\mu_{i,t+1} = w_i + \sum_{p=1}^{n} \Gamma_{i,p} v_{i,t+1-p}^2 + \sum_{q=1}^{q} \Sigma_{i,q} h_{i,t-q}$

2 is $\sum_{p=1}^{n} \Gamma_{i,p} v_{i,t+1-p}^2 + \sum_{q=1}^{q} \Sigma_{i,q} h_{i,t-q}$

2 to insure non-negativity and stationarity some restrictions, such as:
 $\sum_{p=1}^{n} \$ $\begin{aligned} h_{i,\epsilon+1} &= w_i + \sum_{\rho=1}^p \Gamma_{i,\rho} v_{i,\epsilon+1-\rho}^2 + \sum_{q=1}^q \mathrm{S}_{i,q} h_{i,\epsilon-q} \\ \text{Or, } \mathrm{S}_{i,q} &> 0 \quad \text{and} \quad \sum_{p=1}^p \Gamma_{i,p} v_{i,\epsilon+1-\rho}^2 + \sum_{q=1}^q \mathrm{S}_{i,q} h_{i,\epsilon-q} < 1 \\ \text{or, } \mathrm{S}_{i,q} &> 0 \quad \text{and} \quad \sum_{p=1}^p \Gamma_{i,p} v_{i,\epsilon+1-\rho}^2 + \sum_{q=1}^q \$

$$
Q_t = (1 - r - s) \bar{Q} + r \sum_{t-1} r_{t-1} + s Q_{t-1}
$$

where *Q^t* refers to a (*k*×*k*) time varying covariance matrix of *^μ*, Q is the (*k*×*k*) unconditional variance matrix of *i,t u* , and *α* and *β* are nonnegative scalar parameters their estimated standard

rst stage. That is
 $\overline{Q} + \Gamma \sim_{t-1} \sim_{r-1}' + S Q_{t-1}$

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 $\frac{1}{2} Q_t (diag(Q_t))^{-\frac{1}{2}}$
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$$
R_{t} = (diag(Q_{t}))^{-1/2} Q_{t} (diag(Q_{t}))^{-1/2}
$$

(3)

equation of each asset in the sample, nested in a univariate GARCH model of its conditional variance is estimated. Hence, we can define *Dt*as follows:

(5)

, $t / ___\$ who no *it* $\frac{1}{L}$ / $\frac{1}{L}$ w (5)
 $\overline{h_{ii,t}}$ where μ_{it} is then used to estimate the
of the conditional correlation. The evolution
ation in the DCC model is given by: $\sim_{ii} = \frac{V_{i,t}}{\sqrt{1-\mu}}$ where μ_i is then used to estimate the

parameters of the conditional correlation. The evolution of the correlation in the DCC model is given by:

(6)

satisfying $\alpha + \beta < 1$. Since \mathbb{Z}_t does not generally have ones on the diagonal, we scale it to obtain a proper correlation matrix *R^t* . Thus,

$$
\left(7\right)
$$

where $\big({diag}(Q_{_{\!\scriptscriptstyle{I}}})\big)^{\!-\!/\!_2} = {diag}\, \big(1 \! \big/ \sqrt{q_{_{11,t}}}\,........ 1 \! \big/ \sqrt{q_{_{nn,t}}}\, \big)$

$$
...,_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}, \quad i, j = 1, 2, \dots, n, \text{ and } i \neq j
$$
 (8)

Expressing the correlation coefficient in a bivariate case, we have:

However, to insure non-negativity and stationarity some restrictions, such as:
\n
$$
\Gamma_{i,p} > 0; S_{i,q} > 0 \text{ and } \sum_{p=1}^{n} \Gamma_{ip} V_{i,i+1-p}^2 + \sum_{q=1}^{n} S_{i,q} h_{i,-q} < 1
$$
\nshould be imposed. These univariate variance estimates are then used to estimate the
\nare then used instead. Let us use a specific solution to estimate the parameters of the conditional correlation. The evolution
\nmevalues for each asset. In the second stage, return
\nresiduals are transformed by their estimated standard
\ndeviations from the first stage. That is
\n
$$
Q_{i} = (1-r - S) \overline{Q} + r - {}_{i-1}r_{i-1} + S Q_{i-1}
$$
\nwhere Q_{i} refers to a $(k \cdot \theta)$ time varying covariance
\nof $i \ell u$, and α and θ are nonnegative scalar parameters
\nof $i \ell u$, and α and θ are nonnegative scalar parameters
\n $R_{i} = (diag(Q_{i}))^{-1/2} Q_{i} (diag(Q_{i}))^{-1/2}$ \nwhere $(diag(Q_{i}))^{-1/2} = diag(1/\sqrt{q_{11}},......1/\sqrt{q_{m,i}})$
\nwhere $(diag(Q_{i}))^{-1/2} = diag(1/\sqrt{q_{11}},......1/\sqrt{q_{m,i}})$
\n $\cdots_{ij} = q_{ij,i}/\sqrt{q_{ij,j}q_{ji,i}}, i, j=1,2,......n$, and $i \neq j$
\nExpressing the correlation coefficient in a bivariate case, we have:
\n $\cdots_{12,i} = \frac{(1-r - S) \overline{q}_{11} + r - \frac{1}{i,i-1} + S q_{11,i-1} \sqrt{[(1-r - S) \overline{q}_{12} + r - \frac{1}{i,i-1} + S q_{12,i-1}]}{[(1-r - S) \overline{q}_{11} + r - \frac{1}{i,i-1} + S q_{11,i-1}] \sqrt{[(1-r - S) \overline{q}_{12} + r - \frac{2}{i,i+1} + S q_{22,i-1}]}}$ \n(9)
\n α

Bichi, S. & Reuben, O. D. Copyright © 2017 JOSTE. All Rights Reserved (www.atbuftejoste.com)

As per Engle and Sheppard (2001) and Engle (2002), the DCC model can be estimated by using a two – stage approach to maximizing the log - likelihood

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As per Engle and Sheppard (2001) and Engle (2010) and Engle (2011) and Engle (2012) are determined by using a two	functions. Let ϑ denote the parameters in D_i and D_i and D_i are represented by using a two	parameters in R_i then the log likelihood function is given below:
$I_t(u, w) = \left[-\frac{1}{2} \sum_{i=1}^T n \log(2\pi) + \log D_i + v_i'D^{-2}v_i \right] + \left[-\frac{1}{2} \sum_{i=1}^T (\log(2\pi) + \log R_i + v_i'R_i^{-1}v_i) \right]$ \n	(II)	
The first part of the likelihood function in Eq. (II) is volatility, which is the sum of individual GARCH	display negative average weekly returns. More so, the standard deviation in all the cases are greater than the mean, indicating the variables are within the returns maximized in the first stage over the parameter in D_i .	(USB: 4.2688 and NFB: 3.8074). All return series is given the estimated parameters in the first stage where the diagrams is the distance of the first stage.

The first part of the likelihood function in Eq. (10) is volatility, which is the sum of individual GARCH likelihoods. The log – likelihood function can be maximized in the first stage over the parameter in *Dt*. Given the estimated parameters in the first stage, the correlation component of the likelihood function in the second stage (Eq. (8)) can be maximized to estimate correlation coefficients.

RESULTS AND DISCUSSION

Descriptive Statistics of Weekly Return Series

Table 1 contains summary statistics for the returns series in each of the markets. The sample mean in all of the returns are positive and statistically significant because they differ from zero except for the US bond market average weekly return (-0.1042) that

function. Let ϑ denote the parameters in \mathcal{D}_t and w the parameters in R_t , then the log likelihood function is given below: 1: Vol. 5 (2), June, 2017

function. Let ϑ denote the parameters in D_t and w the

parameters in R_t then the log likelihood function is given

below:
 2V_t + $\left[-\frac{1}{2}\sum_{t=1}^T \left(\log(2\Pi) + \log|R_t| + \gamma_t'R_t^{-1} \gamma_t\right)\right]$

$$
g|D_t|^2 + V_t'D^{-2}V_t \left[+ \left[-\frac{1}{2}\sum_{t=1}^T \left(\log(2\pi) + \log|R_t| + \gamma_t'R_t^{-1} \right) \right] \right] \tag{10}
$$

Example of Science, Technology & Education (JOSTE); Vol. 5 (2), June, 2017

So per Engle and Sheppard (2001) and Engle

DCC model can be settimated by using a two

perpeach to maximizing the log - likelihood studies
 $=$ display negative average weekly returns. More so, the standard deviation in all the cases are greater than the mean, indicating the variables are within the returns (USB: 4.2688 and NFGB: 3.8074). All return series display non-zero skewness, the degree of peakedness as indicated by the values of the kurtosis showed that FGNB is more peaked than what is obtained in the normal distribution while the USB is flatter than the normal distribution. Additionally, the Jarque-Bera test results are not significant at 0.01 and 0.05 significance levels, suggesting that the return series for all the markets are not normally distributed. Finally, the calculated values of the ADF test statistics indicate that the level series does not contain a unit root at the 1% and 5% significance levels, implying that the return series are stationary.

* Significant at 5% level ** Significant at 1% and 5% levels

MGARCH DCC (1,1) Results

The bivariate DCC model applied in the analysis allows for a time varying correlation structure. The coefficient *^μ* corresponds to the mean equation parameter, while *α* and *β* represents the US Bond versus FGN Bond. As reflected in Table 2, the sum of the variance equation parameters *αii*and *βii*are not close to 1, which shows the weak persistence of conditional volatility. The estimated conditional correlation (- 0.0545) is negative and very weak, reflecting a weak negative relationship between the two markets (Nigerian

Bond and US Bond Markets). This findings is slightly different from the findings of Engsted and Carsten (2005), where the correlation between US and German monthly excess bond returns over the period 1975 to 2003 is +0.54, which indicates a high degree of co movement of US and German bond markets.**.** Furthermore, the sum of "*α*" and "*β*" is equal to 0.835537. Therefore $\alpha + \beta < 1$ proves the process described to be mean reverting. The implication behind this is that after a shock occurs, the correlations will in time return to the long-run unconditional level.

Log-likelihood*⁼* -1624.92

Note: $ω$, $α$, $β$ are the estimates in Equation (5), $ρ_2$ calculated from Equation (9) and Log-likelihood in Equation (10)

CONCLUSION

This paper analyzed the weekly return volatility spillover between Nigeria and US bond markets by fitting a bivariate DCC-GARCH (1, 1) model. The study discovered a weak negative relationship between the Nigerian and US Bond market returns and proves of mean-reverting process in the time-varying conditional correlation. The paper therefore, contributes to international market relationships, as the volatility co-movement between the

two selected markets has to the best of our knowledge, not been used before. Consequently, bridging the gap in literature and providing more information to investors and intending investors who might want to invest in the Nigeria financial markets and for policy formulation by the federal government on Nigeria.

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