MODELING VOLATILITY TRANSMISSION IN STOCK AND BOND MARKETS OF THE FRONTIER ECONOMIES USING MULTIVARIATE GARCH MODELS

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A DISSERTATION SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES, AHMADU BELLO UNIVERSITY, ZARIA
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DEPARTMENT OF STATISTICS,
FACULTY OF PHYSICAL SCIENCES
AHMADU BELLO UNIVERSITY,
ZARIA, NIGERIA.

JANUARY, 2017.

DECLARATION

I declare that the work in this Dissertation titled “Modeling Volatility Transmission in Stock and Bond Markets of the Frontier Economies Using Multivariate GARCH Models” has been carried out by me in the Department of Statistics. The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this dissertation was previously presented for another degree or diploma at this or any other Institution.

Safiya Ismaila BICHI	___________________	___________________
(Name of Student)	Signature	Date

CERTIFICATION

This Dissertation titled “Modeling Volatility Transmission in Stock and Bond Markets of the Frontier Economies Using Multivariate GARCH Models” by Safiya Ismaila BICHI meets the regulations governing the award of the degree of Masters of Science in Statistics of the Ahmadu Bello University, and is approved for its contribution to knowledge and literary presentation.

Dr. H. G. Dikko Chairman, Supervisory Committee	____________________ Signature	________________ Date
Dr. A. Isah Member, Supervisory Committee	____________________ Signature	________________ Date
Dr. H. G. Dikko Head of Department	____________________ Signature	________________ Date
________________________ External Examiner	____________________ Signature	________________ Date

DEDICATION

I dedicate this work to my mother Mrs. Tabitha I. Bichi and Father Mr. A. Bichi

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I must first give glory to God almighty, the Alpha and Omega for making it possible for me to complete this work. I acknowledge the work of previous authors and papers cited. Also, I sincerely appreciate the intellectual guidance, encouragement and supervision of my supervisors; Dr. H. G. Dikko and Dr. I. Audu who despite their busy schedules have been able to read through the work, make comments and provided the necessary guides that has made this study a huge success. May God bless you and your family (Amen).

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ABSTRACT

The study of volatility transmission between stock and bond markets is not only important for predicting stock returns and bond yields but for understanding the behavior and source of cross-market volatility transmission. This dissertation investigated the different formulations of Multivariate GARCH frameworks and adapted the two most popular used ones – the Baba-Engle-Kraft-Kroner (BEKK)-Generalize Autoregressive Conditional Heteroscedasticity (GARCH) model and the Dynamic Conditional Correlation (DCC)- GARCH model, in studying the dynamics of volatility transmission between Nigerian Stock and Bond Markets , and the Co-movement between United State and Nigeria's bond markets. The study also considered the impact of shocks and volatility from one market to the other as well the long memory volatility of both markets. The study revealed that own past shocks affect the current volatility of the Nigeria stock market and a bidirectional shock transmissions between the Nigerian stock and bond markets, as well as evidence of weak negative relationship between the Nigerian Bond and US Bond Markets. The study also found that the DCC model is a more appropriate model for modeling intra-national volatility transmission (between stock and bond returns) and international transmission of bond market volatility in frontier markets (US and Nigerian bond market). In all, these findings will be informative to investors and Nigeria's federal government for both investment and policy formulation.

TABLE OF CONTENTS

LIST OF TABLES

ABBREVIATIONS

ADF	-Augmented Dickey-Fuller
ARCH	- Autoregressive Conditional Heteroscedasticity
ASEAN	- Association of Southeast Asian Nations
BEKK	- Baba-Engle-Kraft-Kroner
CCC	- Constant Conditional Correlation
DCC	-Dynamic Conditional Correlation
FGNB	-Federal Government of Nigeria's Bond
NFGB	-Nigeria Federal Government Bond
GCC	-Gulf Cooperation Council
GARCH	- Generalized Autoregressive Conditional Heteroscedasticity
GDP	-Gross Domestic Product
MLE	- Maximum Likelihood Estimation
NSE	- Nigeria's Stock Exchange
JB	- Jarque Bera
USB	- United State Government Bond

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

All over the world, financial market plays a vital role in the process of economic growth, through the mobilization of long-term funds for future investment. The Nigerian Market has two-market securities – money market and capital market. The money market is a market for short-term securities while the capital market has long-term securities.

The capital market has over the years, proven to be an important sector that helps in the sustenance of developed and less developed economies since its early development as a financial institution in the 12th century AD in Europe. It mobilizes savings and channels them into productive investments for the development of commerce and industry. As such, the capital market helps in capital formation and economic growth of the country.

The term “frontier markets” was coined by the International Finance Corporation (IFC), a private sector arm of the World Bank Group, in 1992 to reflect a subset of emerging market economies. There is no universal definition of what constitutes the frontier market, but it essentially consists of companies and investments in nations that are economically even less developed than emerging market countries, many of which do not have their own stock exchange. As of September 2013, Morgan Stanley has a list of 28 nations that it classifies in this market, including Nigeria, Croatia, Tunisia, Pakistan and Kenya. Frontier markets are categorically the riskiest markets in the world in which to invest. They have the least number of investors and investment holdings and may not even have a stock market on which to trade.

Although frontier and emerging markets both fall into the same general sector of the global marketplace, there are some critical differences between the two subsectors. Emerging markets offer greater liquidity and stability than frontier markets. But as time progresses, many financial analysts believe some emerging markets have matured to the point where they are moving at least somewhat in tandem with the United States market and fail to provide the level of diversification that they once did. However, frontier markets have slowly but surely started to step in and fill this gap for long-term investors seeking a return on their capital that is largely uncorrelated with the rest of the global economy.

Frontier Markets are investable but have lower market capitalization (usually under 17% of Gross Domestic Product, (GDP)) and liquidity than the more developed "traditional" emerging markets, which makes them inherently riskier investments but also provides potential opportunities for investors to take advantage of privatizations and increased listings on local exchanges over time. As a result, they may also provide better returns. Investments in these markets are thus generally pursued by investors who are seeking higher returns, and who are willing to assume the higher level of risk associated with such markets. Among these risks are political instability, poor liquidity, inadequate regulation, substandard financial reporting, and large currency fluctuations. Apart from risks (currency, liquidity, political and governance risk), investing in frontier markets is a smart diversification to an equity portfolio, as these markets have comparatively less correlation to developed markets, and in good times, can likely beat the returns of other markets. However, frontier markets comprise approximately 2% of global market capitalization and thus remain a very small slice of the global economy.

Frontier markets are also widely diverse in terms of income, geography and degree of economic development. For example, the Gulf Cooperation Council (GCC) countries are among the richest economies globally on a per capita basis, while many of the key Sub-Saharan economies are among the poorest (the average GDP per capita of GCC economies is approximately $43,300 Purchasing Power Parity (PPP) while the average GDP per capita of the frontier Africa and Asia countries is under $2,000 PPP). But the middle class is growing in many frontier markets as improvements in logistics, better access to technology, the spread of mobile phones and better use of natural resources have begun to raise millions out of poverty while boosting consumption trends.

Despite the growing attention to frontier markets among the investment community, very little research actually includes their bond markets. The study of the volatility of their financial market returns is not only important for predicting market returns or bond yields (Fleming et al., 2001 and Cai, *et al.*, 2004), but also help investors understand the behavior and source of cross-market volatility transmission for the purpose of international diversification, risk management, asset pricing and making asset allocation decision. Hence, it is natural to raise the question of measurement of risk and the volatility of returns in frontier market assets and the interdependence across countries.

Since the seminal paper of Engle (1982), Autoregressive Conditional Heteroscedasticity (ARCH), and the Generalized ARCH (GARCH) models proved to be successful in capturing the time-varying variances of economic data in the univariate case. This has motivated many researchers to extend these models to the multivariate dimension (Tse, 2000).

Multivariate volatilities have many important financial applications. Above all, they play an important role in portfolio selection and asset allocation, and they can be used to compute the value at risk of a financial position consisting of multiple assets (Tsay, 2005). So, the application of Multivariate GARCH (MGARCH) models is very wide.

Some of the typical applications are: portfolio optimization (Kroner and Claessens, 1991), pricing of assets (Hafner and Herwartz, 2006) and derivatives, computation of the Value at Risk (Bauwens and Laurent, 2004) futures hedging (Lien *et al*., 2002 and Bera *et al*., 1997). Other applications include volatility transmitting (Karolyi, 1995) and asset allocation, estimation systemic risk in banking (Schröder and Schüler, 2003), determining of the leverage effect (De Goeij and Marquering, 2004), and estimation of the volatility impulse response function (Elder, 2003) etc.

The most obvious application of Multivariate GARCH (MGARCH) models is the study of the relations between the volatilities and co-volatilities of several markets, examining whether the volatility of a particular market leads to the volatility of other markets is the volatility of an asset transmitted to another asset directly (through its conditional variance) or indirectly (through its conditional covariances)? Does a shock on a market increase the volatility on another market, and by how much? Is the impact the same for negative and positive shocks of the same amplitude? A related issue is whether the correlations between asset returns change over time. Are they higher during periods of higher volatility (sometimes associated with financial crises)? Are they increasing in the long run, perhaps because of the globalization of financial markets? Such issues can be studied directly by using a multivariate model that raises the question of the specification of the dynamics of covariances or correlations.

In a slightly different perspective, a few researches have used MGARCH models to assess the impact of volatility in developed financial markets on frontier markets like Nigeria and between stock and bond market of a frontier economy.

1.2 Statement of the Problem

There is a large literature examining the international transmission of equity market volatility, and a growing literature examining the international transmission of bond market volatility, there are relatively few intra-national studies, usually within one asset class. Understanding the nature of linkages between financial markets, both intra-national and international, is fundamental to establishing the limits of diversification, to security pricing, and to successful asset allocation. Nigerians' authors have similarly ignored the intra-national transmission in the financial market while examining the linkages in financial markets. In particular, and to the best of our knowledge, there has been no systematic documentation of the relationship between return volatility in Nigerian stock and bond markets. By contrast to studies of global equity markets, analyses of the interdependence of international bond markets especially of the frontier economies are relatively few in numbers.

It is against this background, that this study seeks to bridge the wide gap in literature and therefore applied the commonly used Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) Framework to model volatility linkages in the Nigerian financial market with a view to selecting the best volatility transmission model for the Nigerian financial market during the sample period. The study also examined the nature of the dynamic relationships between equity and bond price movements both in Nigeria, and the linkage between the developed (US) and frontier markets (Nigeria) with particular reference to the time series behavior of the processes capturing the volatility in each of the two markets.

1.3 Aim and Objectives of the Study

The aim of this study is to model volatility transition in Stock and Bond markets of frontier economy using Multivariate GARCH model. This shall be achieved by the following objectives,

i. To examine how (and indeed whether) the correlation between Nigerian stock and bond market evolves through time.
ii. To determine/find out how shocks in one market affects returns and volatility in other geographical distinct market, examining the dynamic relationships between bond price movement in the Nigeria's bond market and US bond market.
iii. To select and specify the best model for international and intra-national volatility transmission (for examining the nature of the dynamic relationships between stock and bond price movement in the Nigerian financial market, as well as US and Nigerian bond market).

1.4 Significance of the Study

Understanding the impact and the transmission of historical shocks among financial markets, that is, how a shock in one market affect returns and volatilities in other geographically distinct markets, is very important for several reasons. First, in order to determine the persistence of these shocks and the magnitudes of their effects over time, we need to grasp how these innovations are propagated across markets. Second, the analysis of volatility spillovers between markets allows investors to develop effective strategies for hedging against shocks that are propagated across markets. Third, a large shock in one market could destabilize another market if volatility spillover is present across markets. Additionally, it is now widely accepted that financial volatilities move together over time across assets and markets, but recognizing this feature through a multivariate modeling framework leads to more relevant empirical models than working with separate univariate models. From a financial point of view, it opens the door to better decision tools in various areas, such as asset pricing, portfolio selection, option pricing, and hedging and risk management.

1.5 Scope of the Study

Regarding the scope of the study, the result are confined with only two markets, the US and Nigerian markets. The study considered some selected multivariate GARCH models in modeling volatility spillover between the Nigerian stock market (NSE index) and the bond market, and the volatility spillover between the US bond market and the Nigerian bond market. The volatility models considered in this study include: the Baba–Engle–Kraft–Kroner (BEKK), and Dynamic Conditional Correlation MGARCH (DCC-MGARCH).

1.6 Definition of Terms

(i) Heteroskedasticity: This is a situation whereby the variances of the error term of a model are not equal, that is, the variance of the error term varies with time.

(ii) Nigerian Stock Exchange: This is the body responsible for the regulation of stock activities in Nigeria.

(iii) Bond Market: The bond market (also debt market or credit market) is a financial market where participants can issue new debt, known as the primary market, or buy and sell debt securities, known as the secondary market. This is usually in the form of bonds, but it may include notes, bills, and so on.

(iv) Stock Market: A market for the sale and purchase of securities, in which the prices are controlled by the laws of supply and demand.

(v) Capital Market: This is a market in which long – term capital is raised by industry and commerce, the government and local authorities. The money comes from private investors, insurance companies, pension funds and banks and it is usually arranged by issuing houses and merchant banks.

(vi) Interdependence: The term "interdependence" refers to the markets appearing continue level of high correlation during stability period or after the crisis/shocks.

(vii) Risk: Refers to uncertainty as to whether or not an investment choice will perform as expected, particularly due to factors beyond one's control (in other words, the odds an investment will make or lose money).

(viii) Shocks: Liability to change rapidly and unpredictably, especially for the worse.

(vx) Volatility Transmission: The presence of volatility spillover effects that reflects the transmition of risk-pricing between commodities or markets

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents a comprehensive review of both conceptual and empirical works of scholars related to the subject of study. It provides a comprehensive review of literature on development of frontier markets, volatility transmission mechanism across the financial indicators and markets covering country-specific, regional and global level, conceptual framework on modeling the volatility transmission and multivariate GARCH frameworks. These includes an overview of the Nigerian stock and bond markets, financial market volatility transmission, volatility transmission models and review of some related empirical works.

2.2 The Development of Frontier Markets

Frontier markets cover more than twenty-eight nations including Nigeria, Croatia, Tunisia, Pakistan and Kenya (MSCI, 2013). The strong commodity demand and domestic economic growth of these markets make developing economies attractive. According to Eichengreen (2006), the extraordinary stockpile of international reserve in emerging economies helps them to shift from the external deficit to surplus. The damage caused from financial crisis has raised the problem of the lack of well-functioning domestic bond market.

The frontier-market bond consists primarily of sovereign or government debts. The damage caused from financial crisis has raised the problem of the lack of well-functioning domestic bond market. Burger and Warnock (2006) showed the biggest bond market is the US market, which comprises the 42% of the global bond outstanding.

The risk involved in frontier market assets is higher than in emerging and major developed capital markets. Erb *et al.*, (1999) characterized emerging market bonds as having small market capitalization, high volatility, and negative skewness. The extreme risk from several crises such as the Mexican peso crisis of 1994, the Asian currency crisis in 1997/1998, the Russian and the Brazilian bond market bursts of 1998/1999, the crises in Turkey and Argentina of 2000/2001 and so on, raises the importance of an adequate measure of extreme risks in developing markets.

2.3 Conceptual Framework in Multivariate GARCH

Multivariate GARCH models were initially developed in the late 1980s and the first half of the 1990s, and after a period of tranquility in the second half of the 1990s, this area seems to be experiencing again a quick expansion phase. The univariate ARCH model introduced in Engle (1982) has been extended in several directions by allowing for multiple time series, conditional covariance terms in the mean, and own past conditional covariances in each of the covariance equations.

Bollerslev *et al.,* (1988) originally proposed the basic framework of MGARCH which extends the univariate GARCH into the vectorized conditional-variance matrix. This VECH model involves a large number of parameters estimation. In order to make estimation more tractable, Bollerslev *et al.,* (1988) proposed the diagonal VECH model. However, this type of MGARCH model could not be use to examine spillover effects since it simplified the correlation between parameters.

The factor GARCH introduced by Engle *et al.*, (1990) reduces the number of parameters to O(k^2) but empirical studies reveal its poor performance on low land negative correlations. Alexander (2000) further demonstrates how to apply factor (or Orthogonal) GARCH models, which limit the factors accounting for the amount of volatility. The most attractive feature of this kind of MGARCH model is generous enough to provide a method for estimating any variance-covariance matrix using univariate GARCH models. However, Sheppard (2003) criticized this approach in that it is hard to interpret the coefficients on the univariate GARCH model and that it performs poorly for less correlated systems such as individual equities since it reduce the number of parameters to O(k).

Engle and Kroner (1995) made improvements based on the work of Baba Engle, Kraft and Kroner and created a general quadratic form for the covariance equation which successfully eliminated the positive definiteness problem of the original VECH model. In the full general BEKK model, the number of parameters needed to be estimated is O(k^4), the standard BEKK estimation will involve O(k^2) parameters. Other more plausible formulations of BEKK model include diagonal and scalar BEKK where the parameters are restricted to be either diagonal matrices or to be scalars. The most obvious shortcoming of those simplified BEKK models is that some information such as volatility spillover effects are missing in the variance covariance matrix since the parameters have been reduced.

Bollerslev (1990) proposed the Constant Correlation (CC) model; although it still allows volatility time-varying, the conditional correlations are restricted to be time-invariant. Tsui and Yu (1999) have found out that the constant correlation assumption can be rejected for certain assets which indicate that the CC model may not be generous enough.

In light of the pre-mentioned limitations of various MGARCH models, Engle (2002) advocate a new class of MGARCH model which is named as Dynamic Conditional Correlation (DCC). Intuitively, the DCC model maintains the plausibility of the CC model whilst still allowing for time-varying conditional correlation. Sheppard (2003) made a great contribution to the DCC model estimation by reducing the estimation of MGARCH to a series of univariate GARCH process plus an additional correlation estimator. According to Ling and Dhesi (2010), the specification of the univariate GARCH is generous to any GARCH process with normal distribution that satisfies the non-negative constraints and the stationary condition. This recent development is motivated by the usual phenomenon in multivariate modeling of the unequal or mismatching durations of different datasets. Patton (2006) proposed two maximum likelihood estimators (MLEs) of parameters of a multivariate model for time series with histories of different lengths.

In comparing DCC with the BEKK model, it is found that, the prominent strength of the DCC model is that it does not suffer dimension hindrance and could be applied to any dimension. This is because the estimation can be decomposed into two steps: estimating the univariate GARCH and subsequently constructing a maximum likelihood function which has only two parameters. However, the DCC model imposes more restrictions on the type of dynamic effects than the BEKK model. In particular, the conditional variance of returns only depends on the past squared returns, some of which can cause the “volatility spillovers” to be excluded. Similarly, feedback from past volatilities or squared returns on correlations is severely limited in the DCC model (see Micheal, 2010 and (Ling and Dhesi, 2010).). Most scholars chooses the BEKK model to capture the volatility spillover effects and the DCC model to measure the dynamic conditional correlations.

2.4 Volatility Transmission Mechanism Across Markets

Many theories have been proposed to explain how innovations are transmitted between markets. In summary, the contagion in the recent literature is defined as a significant change in the strength of cross-market after a crisis. Therefore, the terms such like linkages, links, co-movement and interdependence are used to describe the financial market relations to each other, while the spillover and transmission refer to the general transmission of shocks between markets.

Interdependence among world stock markets volatility over time and relationships that exist has naturally represented a privileged field for international financial research. Eun and Shim (1989) analyzed daily stock market returns of Australia, Hong Kong, Japan, France, Canada, Switzerland, Germany, the United Kingdom and the United States markets. They found a substantial interdependence between the national markets with United States. According to their finding, the USA market is the most influential market in the world – that makes the country the most important producer of information affecting the world stock market. Ng (2002) provided evidence that emerging Asian stock markets in Indonesia, the Philippines and Thailand have become more closely linked to Singapore. Generally speaking, the correlation of stock market returns across ASEAN markets increased over a period following stock market liberalization. Kuper and Lestano (2007) used the MGARCH, DCC model to examine the financial markets in Thailand and Indonesia. They found correlations between countries within each of the financial market that reveal a certain degree of interdependence among countries, which is lower during crises.

Connolly and Wang (2000) examined the co-movement between returns for the United States, the United Kingdom and Japan's market, conditional on a representative set of macroeconomic news announcement from these three countries. The result shows that the United States market exerts the greatest influence on both on the United Kingdom and Japan's markets, while the United Kingdom's market has more influence on the US market than the Japan's market has. Hoon and Yoon (2013), examined the price returns and volatility linkages between the foreign exchange and stock markets in Korea, using the co-integration test and bi-variate GJR-GARCH (1,1) define the full meaning model based on the BEKK approach. Their results revealed, amongst other things, evidence that a unidirectional volatility spillover exists from the stock market to the foreign exchange market. They also showed that there is no evidence of volatility spillover effect in the pre-crisis, but an evidence of uni-directional volatility spillover effect from the foreign exchange market to the stock market in the post-crisis period, and concluded that financial crisis improves linkages between the two markets. Hemche *et al.*, (2014) examined linkages between the developed and emerging stock markets and found increase in dynamic correlations following the subprime crisis. The contagion hypothesis is not rejected for France, Italy, the UK or Mexico at the level of 1%, and for Argentina at 10%. Pelinescu (2014) applied MGARCH-BEKK on the exchange rate for Romanian, Polish and Czech Republic; and found that covariance correlation is higher in the case of the European markets (Romanian, Polish and Czech Republic).

In considering the impacts of shocks, Hamao *et al.*, (1990) discovered that shocks to the volatility of financial market returns in one country could influence both the conditional volatility and the conditional mean of the returns in another country, while Koutmos and Booth (1995) observed asymmetric volatility relations between the financial markets of the United States, the United Kingdom and Japan, where the influence of negative shocks was different in both scale and direction to positive shocks.

Studies like Lin *et al.,* (1994); Kim *et al.,* (2001); and Forbes and Rigobon (2002) had examined the international transmission mechanism between the United States stock market and its counterpart from industrial countries. Several have documented the leading of the United States stock market for foreign markets and a significant volatility spillover from the United States to foreign countries. Susmel and Engle (1994) examined price and volatility spillover between New York and London using hourly returns, concluded that these spillovers are at best, small and of short duration. Kim and Rogers (1995) examined the change in the transmission of volatility from Japan and the United States to Korea following the liberalization announcement. They used GARCH methodology to inspect the existence of volatility spillover effect on the Korean market from Japan and USA and they found that spillover has increased after the announcement of liberalization especially from Japan. They concluded that the spillover effect is on the volatility of returns more than on returns themselves. Liu and Pan (1997) examined stock return and volatility spillover effects from the United States and Japanese markets to four Asian emerging stock markets, including Hong Kong, Singapore, Taiwan, and Thailand. The result of their study declared that the United States market is more influential than the Japanese market in transmitting return and volatility to the Asian markets. Kanas (1998) studies on the transmission effects among the London, Paris and Frankfurt stock markets concluded that, returns and innovations spillovers are higher during the post-crash time.

Furthermore, Billio and Pelizzon (2003) obtained evidence showing that volatility spillover from the world index return series have increased after the introduction of the European Monetary Union (EMU) for most European stock market. Christiansen (2007) investigated volatility spillover from the United States and aggregate European asset markets into European national asset markets with the innovation of incorporating the bond markets into the analysis. Morales and O'Donnell (2007) examined the volatility spillovers between stock market returns and exchange rate changes for Spain, Portugal, and Italy. They found no significant volatility spillovers from stock returns to exchange rates or vice-versa prior to the introduction of the Euro. However, with the introduction of the Euro, there were significant volatility spillovers from stock returns to exchange rates in all countries for all currencies, with the exception of Portugal in the more recent (2002–2006) period. Mishra, *et al.,* (2007), explored volatility spillovers between the Indian stock and foreign exchange markets. Their results indicated evidence of a bi-directional volatility spillover between the Indian stock market and the foreign exchange market. They concluded that the markets are integrated with each other. Koulakiotis, *et al.*, (2009) found evidence of volatility and error transmission spillover effects from three European financial regions and claim that each region has its own main exporter.

Choi, *et al.*, (2009) in their study of the volatility spillover between New Zealand (NZ) stock market returns and changes in exchange rate using multivariate EGARCH model, found amongst other, evidence of bidirectional volatility spillovers between the NZ stock market returns and NZD/USD exchange rate in the full sample period and in the pre-Asian financial crisis sample period. In contrast to the findings of Choi *et al.*, (2009), Fedorova and Saleem (2010) found evidence of direct linkages between equity markets in terms of both returns and volatility, as well as in the currency markets. They also showed uni-directional volatility spillovers from currency to stock markets in Eastern European markets and in Russia using a bi-variate GARCH-BEKK model. They concluded that there is integration of Eastern European markets within the region and with Russia as well.

Additionally, Arifin and Syahruddin (2011) investigated volatility spillover effects between stock market returns and exchange rate changes within the same economy in the ASEAN-5 countries, during the Asian crisis and the sub-prime crisis, using a bi-variate VAR(1)-GARCH(1,1) model with BEKK representation. They provided evidence to show that exchange rate fluctuations have strong influences on the volatility of stock market. Okpara and Odionye (2012), in their study, appraise the direction of volatility spillover between stock prices and exchange rate in Nigeria. They showed uni-directional volatility spillover running from exchange rate to stock prices. Hoon and Yoon (2012) investigated volatility spillover between stock prices and exchange rates in Asian financial markets and found evidence of bi-directional volatility spillover between two markets in Asia.

In more recent studies, Turkyilmaz and Balibey (2013) examined the relationship between interest rate, exchange rate and stock price using the BEKK-MGARCH approach. They concluded that there is significant transmission of shocks and volatility among the three variables. Ferreira and Leonardo (2014) used MGARCH-BEKK to model volatility transmission between Brazilian and American stock markets. They found evidence of contagion in the indices of Brazil's stock market, increase in the correlation between the indices of the U.S. and Brazilian markets. Olson *et al.,* (2014) also applied the BEKK, CCC, DCC, VIRF in modeling volatility transmission between Goldman Sach's Energy Index and the S&P, he discovered Low S&P 500 returns cause substantial increases in the volatility of the energy index; a weak response from S&P 500 volatility to energy price shocks**.** Bekiros (2014) applied CCC, DCC MGARCH, and BEKK to model currency and stock markets for firms in Taiwan and found ambiguous situation of volatility size effects of the returns to stock prices for large and small firms.

Among the few literature that modeled volatility in frontier markets, Emenike (2014) modeled volatility transmission between Nigeria Stock and Foreign Exchange market. He discovered a uni-directional volatility transmission from foreign exchange market to stock market, which was suggest to be partly because of the import-dependent and mono-production nature of the Nigerian economy. However, the study focused on BEKK-GARCH and did not explore the bond markets

Most studies on bond markets focused on the relationship between mature bond markets and determinant of emerging bond returns. Min (1998) studied determinants of bond spread denominated by dollar in eleven emerging markets and concluded that macroeconomic variables are more influential than the international interest rates. Hunter and Simon (2005) studied the lead-lag relations and the conditional correlations between 10-year US government bond returns and their counterparts from the UK, Germany, and Japan, and found the mean spillover effect is not significant in all countries, implying the contemporary relationships between US and individual industrial country. They also found that the US bond market led both German and Japanese bond markets. Skintzi and Refenes (2006) applied the EGARCH, DCC model in examining the spillover effect in the US and European bond markets, and found significant volatility spillover exist from both the aggregate Euro area bond market and the US bond market to the individual European markets.

Arora and Cerisola (2001) examined the impact of US monetary policy by using sovereign bond spreads as the proxy for the country's risk and the US federal fund target rate as the proxy for the US monetary policy. They discovered domestic fundamentals are the most important factor affecting the country's risk and that the US monetary policy influences the sovereign bond spread.

Other interesting empirical studies contributions on examining volatility spillovers effects could be found in, Bae *et al.,* (2003), Lee (2006), Engle and Sheppard (2001), Steely (2006), Sun and Zhang (2009), Tse and Tsui (2009) e.t.c.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Data Description

The data used in this study are weekly observations on the Nigerian Stock Exchange (NSE) share price index and 10-year Federal Government of Nigerian (FGN) bond yield from August 6, 2010 to December 3, 2015. As well as the weekly observations of the 10-year US and Nigerian Federal Government bond yield from December 14, 2007 to December 27, 2014, representing the return on bonds weekly data in developed and frontier markets respectively. The data for the NSE share price index, 10-year Nigeria bond returns and 10 years US bonds return are available on http://www.tradingeconomics.com

3.2 Computation of Return Series from Price

Each compounded weekly return of each series of each index is generated as follows;

$$r_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

where r_t is the return for period t; P_t and P_{t-1} are price index on week *t* and *t-1* respectively, and *ln* is the natural logarithm.

3.3 Time Series

A time series is a sequence of numerical data points in successive order, usually occurring in uniform intervals e.g. daily, weekly, monthly, quarterly, yearly, etc. Time series methods take into account possible internal structure of the data. Time series analysis is used for many applications such as: economic forecasting, budgetary analysis, stock market analysis, process and quality control, yield projections, etc.

3.4 Stylized Facts of Financial Time Series Data

Financial data exhibits features like:

i. Volatility clustering: Volatility does not keep constant. It is quite common that high returns tend to be followed by high returns and low returns tend to be close with low returns.
ii. Leptokurtosis effect: By viewing the value of kurtosis, one can conclude that the return series can show the feature of fat tails relative to the normal distribution as high kurtosis indicates a larger possibility of extreme movements.
iii. Leverage effect: Volatility increases more after low returns than after high returns. A simple explanation for this is that negative returns imply a larger proportion of debt which leads to a high volatility after smaller changes.
iv. Skewness: All of three variables show evidence of some degree of skewness. The effect of skewness may be positive or negative, which describes their departure from symmetry.
v. Long-run memory effect: The existence of this effect reflects persistence temporal dependence even between distant observations.

3.5 Test for Normality

Jarque- Bera test is the commonly used diagnosis statistic to test for normality of the residuals. It measures the difference of the skewness and kurtosis of the series with those of the normal distribution. The test statistic is computed as:

$$JB = \frac{n}{6}\left[S^2 + \frac{(K-3)^2}{4} \right] \tag{3.2}$$

and is approximately χ_2^2. S is the skewness and K is the kurtosis.

$$K = \frac{\mu_4}{\mu_2^2} - 3 = \frac{\mu_4}{\sigma^4} - 3 \tag{3.3}$$

It is platykurtic if $K < 3$; leptokurtic if $K > 3$; and mesokurtic if $K = 3$.

We reject the null hypothesis of normality if the Jarque- Bera statistic exceeds the corresponding critical value.

3.6 Multivariate GARCH Models

Multivariate GARCH models explains specifically how the covariances move over time. According to Pourahmadi (1999), modeling a covariance matrix is difficult because of the likely high dimensionality of the problem and the constraint that a covariance matrix must be positive definite. The crucial stage in MGARCH modeling is to provide a realistic but parsimonious specification of the variance matrix ensuring its positivity. A disadvantage of the multivariate approach is that the number of parameters to be estimated in the GARCH equation increases rapidly. This limits the number of assets that can be included (De Goeij and Marquerung, 2004).

There are three approaches for constructing multivariate GARCH models (Bauwens *et al.,* 2006). First, direct generalizations of the univariate GARCH model of Bollerslev (1986) such as VECH, BEKK and factor models, flexible MGARCH, Riskmetrics, Cholesky and full factor GARCH models. Second, linear combinations of univariate GARCH models such as (generalized) orthogonal models and latent factor models. Third, nonlinear combinations of univariate GARCH models such as constant and dynamic conditional correlation models, the general dynamic covariance model and copula-GARCH models.

The different specifications of MGARCH models can be divided into four categories as suggested by Annastiina and Timo, (2008). The first one, the conditional covariance matrix is modeled directly. This class includes, in particular, the VEC and BEKK models, which are also the first parametric MGARCH models. The models in the second class – the factor models, are motivated by parsimony: the process r_t is assumed to be generated by a (small) number of unobserved heteroskedastic factors. Models in the third – models of conditional variances and correlations; are built on the idea of modeling the conditional variances and correlations instead of straightforward modeling of the conditional covariance matrix. Members of this class include the Constant Conditional Correlation (CCC) model, DCC model and other extensions of CCC model. The appeal of this class lies in the intuitive interpretation of the correlations, and models belonging to it have received plenty of attention in the recent literature. Finally the semi and nonparametric approaches; this can offset the loss of efficiency of the parametric estimators due to misspecified structure of the conditional covariance matrices (see Chib, *et al.,* 2008).

3.7 Multivariate GARCH Models Used

To achieve the objectives of this work, the most widely used models of conditional covariance and correlation in the multivirate GARCH class: BEKK-MGARCH and DCC-MGARCH (Alexander, 2008; Micheal, 2010). Additionally, they have the abilities to capture the leptokurtic, autocorrelation features of financial time series, and they are known to proffer a time-varying variance-covariance matrix, which reveals various pieces of information about volatility and correlation (Ling and Dhesi, 2010).

3.7.1 Baba–Engle–Kraft–Kroner (BEKK)

A model of the conditional covariance matrix that can be view as a restricted version of the VEC model is the Baba-Engle-Kraft-Kroner (BEKK) defined in Engle and Kroner (1995). It has the attractive property that the conditional covariance matrices are positive definite by construction. The first step in the multivariate GARCH methodology is to specify the mean equation. Thus, the mean equation for return series is specified as follows:

$$R_t = \mu_i + \theta R_{i,t-1} + \varepsilon_t; \qquad \varepsilon_t = H_t^{1/2}\eta_t \tag{3.4}$$

where: $R_t = \; R_t^S, R_t^B \;'$ is a vector of returns of the Nigerian stock and Bond markets respectively, θ refers to a 2 x 2 matrix of coefficients, $\varepsilon_t = \; \varepsilon_t^S \varepsilon_t^B \;'$ is the vector of error terms of conditional mean equation for stock and bond markets returns respectively. $\eta_t = \; \eta_t^S \eta_t^B$ is a sequence of independently and identically distributed (i.i.d) random errors; $H_t = \begin{pmatrix} h_t^S & h_t^{SB} \\ . & h_t^B \end{pmatrix}$ is conditional variance-covariance of stock and bond market returns.

Similarly, $R_t = \; R_t^{UB}, R_t^{NB} \;'$ is a vectors of returns of the US and Nigerian bond markets respectively, θ refers to a 2 x 2 matrix of coefficients, $\varepsilon_t = \; \varepsilon_t^{UB} \varepsilon_t^{NB} \;'$ is the vector of error terms of conditional mean equation for US and Nigerian bond markets returns respectively. $\eta_t = \; \eta_t^{UB} \eta_t^{NB}$ is a sequence of independently and identically distributed (i.i.d) random errors; $H_t = \begin{pmatrix} h_t^{UB} & h_t^{UBNB} \\ . & h_t^{NB} \end{pmatrix}$ is conditional variance-covariance of US and Nigerian bond market returns.

The next step is to specify the conditional variance-covariance equation. Thus, the BEKK representation of Multivariate GARCH (1,1) model is given by:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \tag{3.5}$$

where: H_t is the conditional variance matrix. C, A, and B are parameter matrices. C is a 2×2 lower triangular matrix, A is 2×2 square matrix that shows how conditional variances correlate with past squared errors, and B is 2×2 square matrix that measures the effect of past conditional variances on the current conditional variances and the degree of persistence in the volatility of the markets. The parameter matrices can be represented as follows:

$$\begin{pmatrix} h_{11,t} & h_{12,t} \\ . & h_{22,t} \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} \\ 0 & C_{22} \end{pmatrix}' \begin{pmatrix} C_{11} & C_{12} \\ 0 & C_{22} \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \tag{3.6}$$

where: $h_{11,t}$ denotes the conditional variance of the stock market, $h_{12,t}$ the covariance of stock and bond markets, and $h_{22,t}$ the conditional variance of the bond market. The significance of the diagonal coefficients $a_{11,t}\,(a_{22,t})$ suggests that the current conditional variance of $h_{11,t}$ ($h_{22,t}$) is correlated with its own past squared errors, while the significance of the lagged variance $b_{11,t}\,(b_{22,t})$ indicates that the current conditional variance of $h_{11,t}\,(h_{22,t})$ is affected by its own past conditional variance. Likewise, the significance of the off-diagonal coefficients $a_{12,t}$ and $b_{12,t}$ indicates evidence of shock and volatility transmission effects from the stock market to the bond market, whereas the significance of the off-diagonal coefficients $a_{21,t}$ and $b_{21,t}$ shows evidence of volatility transmission effects from the bond market to the stock market.

Similarly, as in Equation (3.6), $h_{11,t}$ denotes the conditional variance of the US bond market, $h_{12,t}$ the covariance of US and Nigeria's bond markets, and $h_{22,t}$ the conditional variance of the Nigeria's bond market. The significance of the off-diagonal coefficients $a_{12,t}$ and $b_{12,t}$ indicates evidence of shock and volatility transmission effects from the US bond market to the Nigerian bond market, whereas the significance of the off-diagonal coefficients $a_{21,t}$ and $b_{21,t}$ shows evidence of volatility transmission effects from the Nigeria's bond market to the US bond market.

The parameter matrices are estimated using the expanded BEKK-MGARCH (1,1) equation:

$$h_{11,t+1} = c_{11}^2 + a_{11}^2\varepsilon_{1,t}^2 + 2a_{11}a_{12}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2\varepsilon_{2,t}^2 + b_{11}^2h_{11,t}^2 + 2b_{11}b_{12}h_{12,t} + b_{21}^2h_{22,t} \qquad (3.7)$$

$$h_{22,t+1} = c_{12}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2\varepsilon_{2,t}^2 + b_{12}^2h_{11,t}^2 + 2b_{12}b_{12}h_{12} + b_{22}^2h_{22,t} \qquad (3.8)$$

Equations (3.7) and (3.8) show how shocks or volatilities are transmitted between the stock market and bond market in Nigeria. The significance of the off-diagonal parameters is evidence of shock and volatility transmission between the two markets.

Again, the Equations (3.7) and (3.8) also show how shocks or volatility are transmitted between the US and Nigerian bond markets and the significance of the off-diagonal parameters is evidence of shock and volatility transmission between the two markets.

The parameters are estimated using the maximum likelihood estimation method optimized with the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm. The conditional likelihood function L(θ) is expressed thus:

$$L\ \ \theta\ \ = -T\ln\ \ 2\prod\ \ -\tfrac{1}{2}\sum_{t=1}^{T}\ \ln\left|h_t\right| + \varepsilon_t{}' H_t^{-1}\varepsilon_t \qquad (3.9)$$

where: T is the number of observations and θ is the parameter vector to be estimated.

3.7.2 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 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 stock market return and bond markets (US and Nigeria) returns are multivariate normally distributed with zero mean and conditional variance-covariance matrix H_t. Our multivariate DCC-GARCH model can be presented as follows:

$$r_t = \mu_t + \varepsilon_t \tag{3.10}$$

with $\varepsilon_t \mid \Omega_{t-1} \rightarrow N\ 0, H_t$ where, r_t is the (k×1) vector of the returns, ε_t is a (k×1) vector of zero mean return innovations conditional on the information, Ω_{t-1} available at time t-1 and the conditional variance-covariance matrix (H_t) in the DCC model can be expressed as:

$$H_t = D_t R_t D_t \tag{3.11}$$

where D_t represents a (k×k) diagonal matrix of the conditional volatility of the returns on each asset in the sample and R_t is the (k×k) conditional correlation matrix.

The DCC-GARCH model estimates conditional volatilities and correlations in two steps. In the first step the mean equation of each asset in the sample, nested in a univariate GARCH model of its conditional variance is estimated. Hence, we can define D_t as follows:

$$D_t = \ h_{iit}^{1/2} ......h_{kkt}^{1/2} \tag{3.12}$$

where: h_{iit}, conditional variance of each asset, is assumed to follow a univariate GARCH p_i, q_i process, given by the following expression:

$$h_{i,t+1} = w_i + \sum_{p=1}^{p_1} \alpha_{i,p} \varepsilon_{i,t+1-p}^2 + \sum_{q=1}^{q_1} \beta_{i,q} h_{i,t-q} \tag{3.13}$$

however, to Ensure non-negativity and stationarity some restrictions, such as:

$$\alpha_{i,p} > 0;\ \beta_{\mathrm{i,q}} > 0 \text{ and } \sum_{\mathrm{p=1}}^{\mathrm{p_1}} \alpha_{\mathrm{i,p}} \varepsilon_{i,t+1-p}^2 + \sum_{q=1}^{q_1} \beta_{i,q} h_{i,t-q} < 1$$

should be imposed. These univariate variance estimates are then used to standardize the zero mean return innovations for each asset.

In the second stage, stock return residuals are transformed by their estimated standard deviations from the first stage. That is $\mu_{it} = \varepsilon_{i,t} \big/ \sqrt{h_{ii,t}}$ where μ_{it} is then used to estimate the parameters of the conditional correlation. The evolution of the correlation in the DCC model is given by:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\mu_{t-1}\mu_{r-1}' + \beta Q_{t-1} \tag{3.14}$$

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 satisfying $\alpha + \beta < 1$. Since Q_t does not generally have ones on the diagonal, we scale it to obtain a proper correlation matrix R_t . Thus,

$$R_t = \{diag(Q_t)\}^{-1/2} Q_t \{diag(Q_t)\}^{-1/2} \tag{3.15}$$

where $\{diag(Q_t)\}^{-1/2} = diag\left(1\big/\sqrt{q_{11,t}} ....1\big/\sqrt{q_{nn,t}}\right)$

Finally, the conditional correlation coefficient ρ_{ij} between two assets i and j is then expressed by the following equation:

$$\rho_{ij,t} = q_{ij,t} \Big/ \sqrt{q_{ii,t} q_{jj,t}}, \quad i, j = 1,2,.......n, \text{ and } i \neq j \tag{3.16}$$

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

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1,t-1}\mu_{2,t-1} + \beta q_{12.t-1}}{\sqrt{\left[(1-\alpha-\beta)\bar{q}_{11} + \alpha\mu_{1.t-1}^{2} + \beta q_{11.t-1}\right]}\sqrt{\left[(1-\alpha-\beta)\bar{q}_{22} + \alpha\mu_{2.t-1}^{2} + \beta q_{22.t-1}\right]}} \tag{3.17}$$

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 function. Let θ denote the parameters in D_t and ϕ the parameters in R_t, then the log likelihood function is given below:

$$I_t(\theta,\phi) = \left[-\frac{1}{2}\sum_{t-1}^{T} n\log(2\Pi) + \log|D_t|^2 + \varepsilon_t' D^{-2}\varepsilon_t\right] + \left[-\frac{1}{2}\sum_{t-1}^{T}\left(\log(2\Pi) + \log|R_t| + \mu_t' R_t^{-1}\mu_t\right)\right] \tag{3.18}$$

The first part of the likelihood function in Equation (3.18) 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 D_t. Given the estimated parameters in the first stage, the correlation component of the likelihood function in the second stage (the second part of Equation (3.18)) can be maximized to estimate correlation coefficients.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents a detailed analysis of the data collected. The first part contains the properties of the market returns including the coefficient of skewness, kurtosis to check presence of typical stylized facts and test for unit root. The second part fits the specified MGARCH models: MGARCH (1,1) - BEKK and MGARHC DCC (1,1) to the stock returns and bond yields. In the final part, we evaluated and selected the appropriate model for modeling volatility transmission between: Nigerian Stock and Bond market, and US and Nigerian Bond market.

4.2 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 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 (for NSE: 2.7316; FGNB: 6.963; USB: 4.2688 and NFGB:3.8074).

Additionally, all return series display non-zero skewnes. The degree of peakedness or flatness as indicated by the values of the kurtosis showed that NSE, FGNB and NFGB are more peaked than what is obtain in the normal distribution while the USB is flatter than the normal distribution. Finally, 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.

Table 4.1: Descriptive Statistics of the Weekly Returns

Statistics	Markets			
	NSE	FGB	USB	NFGB
Mean	0.020	0.112	-0.104	0.061
Maximum	15.615	63.104	15.468	28.582
Minimum	-13.955	-64.933	-16.461	-22.957
Std. Deviation	2.732	6.963	21.498	0.344
Skewness	0.136	0.110	-0.124	1.623
Kurtosis	8.106	51.012	1.569	20.202
J-B Statistics (Probability)	770.260 (5.48e-168)	30.469 (0.0000)	32.798 (7.55e-008)	5442.8 00 (0.0000)
Observations	281	281	312	312
ADF	9.952**	-11.408**	-8.920**	-9.338**

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

4.3 Unit Root Test Results

Before the Multivariate GARCH (1,1) model is estimated, it is necessary to check the stationarity of the variables. This step is to ensure that the series are stationary because estimates obtained from non-stationary series are not reliable. Table 4.1 also shows the results of the Augmented Dickey-Fuller (ADF) unit root test for the return series. The null hypothesis of the ADF test is that a time series does not contains a unit root. As shown in Table 1, 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.

4.4 MGARCH (1,1)-BEKK Results

The results of the Multivariate GARCH (1,1)-BEKK model employed to investigate the nature of volatility transmission between the Nigerian Stock and Bond Market, and US

Bond and Nigerian Bond Markets are shown in Table 4.2 and Table 4.3. Notice from Table 2 that the estimates of all the diagonal parameters, only a_{11} is significant at 5% significant level, indicating that the own past shocks affect the current volatility of the Nigeria stock market. However, a_{22} and b_{11}, b_{22}, are all not statistically significant at both 5% and 1% significant levels, suggesting that own past volatility does not affect the current volatility of the stock and bond exchange markets in Nigeria.

The off-diagonal elements of matrices A and B capture cross-market shock and volatility transmission between the markets. From the off-diagonal elements of matrix A (a_{12} and a_{21}), we see evidence of bi-directional shock transmissions between the Nigerian stock and bond markets at 5% significance level. This suggests that information flow in the bond market also impacts the stock market. In the same way, shocks in the stock market affect the bond market. Evidence of bi-directional shock transmission between stock and bond markets are not surprising given advances in information and communication technology (ICT) in the Nigerian financial markets. It is thus very easy for information to flow between the two markets. This finding provides new insight into the interaction of volatility shocks among stock and bond markets in Nigeria.

Similarly, as shown in Table 4.3, the diagonal elements of matrix A and B, are all not statistically significant at both 5% and 1% significant level. This suggests that the current conditional variance is not correlated with its own past squared errors and it is not affected by its own past conditional variance. In other words, the own past volatility does not affect the current volatility of the Nigerian and US bond markets. The off-diagonal element of matrix A and B are also not statistically significant at both 5% and 1% significant level, suggesting that shocks in the current value of conditional volatility of the US bond market does not depend on past volatility and does not affect shocks in the Nigerian bond market. Likewise, shocks in the Nigerian bond market do not affect shocks in US bond market.

Table 4.2: Estimated Results of the GARCH-BEKK Model for NSE and FGN Bond Markets

Parameter	Coefficient	Std.Error	t-value	P-value
c_{11}	1.657	0.255	6.492	0.000**
c_{12}	-0.519	0.741	-0.700	0.484
c_{22}	4.514	-1.897	-2.379	-0.018*
a_{11}	-0.405	0.183	2.140	0.028*
a_{21}	0.462	0.149	3.100	0.002**
a_{12}	0.791	0.372	2.124	0.035*
a_{22}	-0.156	0.361	-0.432	0.666
b_{11}	0.093	0.561	0.165	0.869
b_{21}	-0.216	0.528	-0.409	0.683
b_{12}	0.064	0.427	0.149	0.882
b_{22}	0.308	0.694	0.445	0.657

Notes. a_{ij} and b_{ij} are the corresponding ARCH and GARCH parameters for each market. *Significant at 5% level; **significant at both 1% and 5% levels.

Table 4.3: Estimated Results of the GARCH-BEKK Model for US Bond and Nigerian FG Bond Markets

Parameter	Coefficient	Std.Error	t-value	t-prob
c_{11}	2.139	0.281	7.621	0.000 **
c_{12}	0.309	0.367	-0.844	0.399
c_{22}	3.682	0.421	8.747	0.000**
a_{11}	0.579	0.508	1.141	0.255
a_{21}	0.099	0.406	0.245	0.807
a_{12}	-0.456	0.473	-0.964	0.336
a_{22}	-0.113	0.340	-0.333	0.739
b_{11}	0.138	0.164	-0.843	0.399
b_{21}	0.242	0.151	1.606	0.109
b_{12}	0.255	0.205	1.247	0.213
b_{22}	-0.119	0.135	- 0.876	0.382

Note: *Significant at 5% level and **significant at both 1% and 5% levels.

4.5 MGARCH DCC (1,1) Results

Finally, we reported the results of estimating the complete MGARCH DCC model. Table 4.4 and Table 4.5 report Nigerian stock and Bond markets, and US Bond and Nigerian Bond markets respectively. 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 conditional variance of NSE versus FGN Bond, US Bond versus FGN Bond correspondingly.

As reflected in the Table 4.4, all parameters are positive except for α_1 and β_2. Only 3 parameters are found to be significant at the various levels of significance**.** The significance of mean equation parameter μ shows the dependence of returns on their lag returns. Furthermore, the volatility persistence in these markets is measured by ($\alpha + \beta$), and looking at Table 4.4, the sums of the variance equation parameters α_{ii} and β_{ii} are not close to 1, indicating rather weak persistence in conditional variances. The estimated conditional correlation is negative (-0.025516) and not significant, reflecting a weak negative relationship between the Nigerian Stock and Bond Markets and the sum of “a” and “b” is equal to 0.94671. Indicating that the process is mean reverting- after a shock occurs the correlations will in time return to the long-run unconditional level, since a + b < 1.

Again, Table 4.5 displays estimation results for the DCC (1, 1) model for US Bond and FGN Bond yields. The sum of the variance equation parameters α_{ii} and β_{ii} are not close to 1, which shows the weak persistence of conditional volatility. The estimated conditional correlation is negative (-0.0545) and not significant, reflecting a weak negative relationship between the two markets (Nigerian Bond and US Bond Markets). Furthermore, the sum of “a” and “b” is equal to 0.835537. Indicating that the process is mean reverting- after a shock occurs the correlations will in time return to the long-run unconditional level, since a + b < 1.

Table 4.4: Bivariate DCC(1,1) Estimation Results between the Nigerian Stock and Bond Markets

Parameter	Coefficient	Std.Error	t-value	t-prob
μ_1	0.183	0.163	1.121	0.263
μ_2	2.182	0.421	5.187	0.000**
ω_1	1.060	0.505	2.100	0.037*
ω_2	0.059	0.059	0.984	0.326
α_1	0.804	0.351	2.292	0.023*
α_2	-0.153	0.293	-0.523	0.602
β_1	-0.594	0.310	-1.917	0.056*
β_2	0.369	0.249	1.484	0.139
A	0.045	0.027	1.611	0.108
B	0.902	0.043	20.780	0.000
ρ_{21}	-0.026	0.101	-0.252	0.801

Note: ω, α, β are the estimates in Equation (3.10) and ρ is calculated from Equation (3.14) and Log-likelihood in Equation (3.15)

Table 4. 5: Bivariate DCC(1,1) estimation results between US Bond and Nigerian Bond Markets

Parameter	Coefficient	Std.Error	t-value	t-prob
μ_1	-0.011	0.265	-0.038	0.969
μ_2	1.766	0.906	1.948	0.052
ω_1	0.110	0.040	2.749	0.006*
ω_2	0.789	0.053	14.750	0.000**
α_1	0.744	0.494	1.506	0.133
α_2	-0.019	0.432	-0.043	0.965
β_1	-0.559	0.471	-1.187	0.236
β_2	0.191	0.393	0.487	0.627
A	0.000	0.000	0.000	1.000
B	0.836	21.904	0.038	0.969
ρ_{21}	-0.055	0.055	-0.996	0.320

Log-likelihood = -1624.92

Note: ω, α, β are the estimates in Equation (3.10) and log-likelihoods are calculated from Equation (3.17) and Log-likelihood in Equation (3.18)

4.6 Model Selection

We compared the two models applied for modelling the Nigerian Stock and Bond Markets according to their goodness-of-fit statistics, namely Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (SBC) (shown in appendix A and B). The DCC model had the smallet value for both criteria, which suggests that the DCC model was indeed the best performer for modelling the NSE and Bond Markets.

Likewise, the Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (SBC) was applied to test the goodness-of-fit statistics of the

BEKK and DCC in modeling the volatility transmission between the US and Nigerian Bond Market (see appendixes C and D) and the the DCC model was indeed the best performer, having the smaller value for both criteria.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Summary

In this study, the transmission between Nigerian Stock and Bond Markets, and US Bond and Nigerian Bond Markets was examined from two aspects: volatility spillover effects and time-varying correlation. The basic descriptive statistic and preliminary tests guide us to employ the most popularly used MGARCH type models. In particular, the BEKK (1,1) and DCC (1,1) to accomplish our empirical study based on the critical review of different type of Multivariate GARCH models. Findings showed that there is a significant bi-directional shock transmission between stock and bond markets while a weak negative relationship was found between the Nigerian Bond and US Bond Markets. Additionally, evidence found proves that there is mean-reverting process in the time-varying conditional correlation between the Nigerian bond and US bond markets.

The study provides some interesting findings which contribute to the understanding of the time-varying nature of volatility spillover effects between Nigerian stock and bond returns, and Nigerian bond and US bond returns. Although the study reveals that though both BEKK and DCC- MGARCH are useful in determining volatility linkages between both markets, DCC-MGARCH model was indeed the best performer for modeling linkages in both markets. These relationships provide opportunity for investors to apply hedging strategy as well as diversifying their investment portfolio for better returns particularly where these correlations are found to be negative between markets.

5.2 Conclusion

This study had examined the weekly return volatility spillover between stock and bond markets of frontier economies and between bond markets of frontier and developed economies. We discovered a bi-directional volatility spillover between the stock and bond markets, and weak negative relationship between the two bond markets. We compared the two models applied for modeling both the Nigerian Stock and Bond Markets and USB and FGN Bond Markets according to their goodness-of-fit statistics, namely Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (SBC) (shown in appendix A and B) and the DCC was the most suitable for modelling volatility transmission between both markets.

In all, the findings are very crucial and informative to investors and intending investors who might want to invest in frontier markets and for policy formulation by governments of frontier countries.

5.3 Recommendations

1) This study recommends the application of Corporate Bonds, issued by private and/or public companies. They normally have higher interest rates than government bonds. Some corporate bonds can be converted to equity if certain provisions are met – such bonds are called convertible bonds.
2) Government policies on either the Nigeria's stock or Bond market should be review with caution as the empirical study reveals that shocks in either of the above markets affects the other.
3) The study found that volatility is inherent therefore suggest the application of other MGARCH models and further work on the models with more updated data

as well as to explore other frontier markets. This will better inform investors, intending investors and investment analyst as volatility spillover is the major index used to evaluate market linkages and co-movements.

5.4 Contribution to Knowledge

We believe that the results of this study make its contribution to:

i. linkages in frontier and global economy scrutinizing (international transmission in bond markets);
ii. intra-market relationships in the frontier economy, as the selected markets in the countries for this study have to the best of our knowledge not been used before, revealing the unique results gained and bridging the gap in literature.

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APPENDICES

Appendix A: Diagnostics and Information Criteria for BEKK for Nigerian Stock and Bond Markets

Information Criteria (to be minimized)
Akaike 9.486682 Shibata 9.480651
Schwarz 9.693848 Hannan-Quinn 9.569767

Appendix B: Diagnostics and Information Criteria for DCC for Nigerian Stock and Bond Markets

Information Criteria (to be minimized)
Akaike 0.159185 Shibata 0.152406
Schwarz 0.379299 Hannan-Quinn 0.247463

Appendix C: Diagnostics and Information Criteria for BEKK for Nigerian and US Markets

Information Criteria (to be minimized)
Akaike 10.349527 Shibata 10.347152
Schwarz 10.481492 Hannan-Quinn 10.402269

Appendix D: Diagnostics and Information Criteria for DCC for Nigerian and US Markets

Information Criteria (to be minimized)
Akaike 0.173238 Shibata 0.164140
Schwarz 0.437168 Hannan-Quinn 0.278723