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Modelling Volatility Spillovers from Developed stock markets to Selected African Stock Markets

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DECLARATION

I hereby declare that, the thesis is my original work and all sources and materials used for writing it have been duly acknowledged. I declare that I have not so far submitted this thesis to any other institution anywhere for the award of any academic degree, diploma or certificate.

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Acronyms

ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AIC	Akakie Information Criteria
AR	Autoregressive
ARCH	Autoregressive Conditionally Heteroskedasticity
ARMA	Autoregressive Moving Average
BEKK	Baba, Engle, Kraft and Kroner
BIC	Bayesian Information Criteria
CCC	Constant Conditional Covariance
CGARCH	Component Generalized Autoregressive Conditionally Heteroskedasticity
DCC	Dynamic Conditional Covariance
Ems	Emerging Markets
HQ	Hannan-Quinn
IC	Information Criteria
LB	Ljung-Box
LM	Lagrange Multiplier
MGARCH	multivariate generalized autoregressive conditionally heteroskedasticity
OLS	Ordinary Least Square
PP	Phillip- Perron
SA	South Africa
USA	United States Of America
USDX	United States Dollar Index
VAR	Vector Autoregressive

Modelling Volatility Spillovers from Developed stock markets to Selected

African Stock Markets

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ABSTRACT

International stock markets have been characterized by increasing degree of integration. However, stock markets have been new phenomenon in Africa (more than half of African stock markets have been opened in the last decade). Development of stock market has an important role in promoting economical growth in the country. Due to financial linkage between stock markets, volatility could be spillovers from one to another. Thus, the main purpose of this thesis is to model volatility spillovers from developed stock markets to selected African stock markets using MGARCH models. The data for this purpose is weekly closing return data obtained from Bloomberg and span during the period from 1999 week 1 to 2017 week 46. Among many MGARCH methodologies to analysis volatility spillover, the conditional correlation model like CCC and DCC model are used in this study. Tri-variate VAR (1) model is fitted for the mean equation and have no serial correlation in the residuals while there were correlation in the squared residuals (ARCH effect) that is presence of volatility in the return data. The volatility of stock market returns was captured by Tri-variate DCC (1, 1) with t-distribution having 6 degree freedom in this thesis. From the results we concluded that there are volatility spillover from USA to South Africa, Europe to morocco and Europe to South Africa stock market returns. And volatility spillovers among those stock markets are strong and increasing over time in the study period. In sum volatility is spillovers from developed stock market returns to selected African stock markets except for Nigeria and Kenya and which agrees the finding of this thesis. This thesis attempts to recommend that further researcher could be investigate the volatility spillover from developed stock market to African stock market using conditional covariance model like BEKK and diagonal VECH and considering world financial crisis like 2008, to investigate volatility spillover effect before and after crisis . Last but not least, this thesis suggests further researcher would be dividing the study period in to two subsamples and forecasting volatility spillover.

1. INTRODUCTION

1.1 Background of the Study

Stock markets are a comparatively new phenomenon in Africa (more than half of African stock markets have been opened in the last decade), development of these markets has been considered an essential component of financial sector development and is expected to play an important role in promoting the growth of African economies (Jefferis, 1995; Kenny and Moss, 1998; Piesse and Hearn, 2002). Obviously, how well the African stock markets function plays a crucial role in determining their contributions to economic growth. International financial markets have been characterized by increasing degrees of integration. However, Sub-Saharan Africa has been lagging behind. Its financial markets have been considered fairly independent, so that, just before the start of the subprime crisis, the Economist characterized Africans as the final frontier of globalization for international investors, suggesting to "Buy Africa" to diversify their risk. Indeed, before the global financial meltdown, African financial markets had experienced a large expansion in a very short time. The number of operating stock exchanges in Africa rose from just eight in 1989, to 23 in 2007, reaching a total market capitalization of over $2.1 billion. Despite their relatively small size and low liquidity during the last few years-many African markets offered very large returns to investors. There has been at least one African stock market in the top 10 best-performing markets in the world every year since 1995. In 2004, for example, six African countries (Ghana, Uganda, Kenya, Egypt, Mauritius and Nigeria) were among the world's 10 best-performing stock markets, while in 2005, Egypt, Uganda and Zambia were in the top five. The global financial crisis has nevertheless reached Africa, hitting some of the drivers of African countries' development. In 2008, foreign direct investment and portfolio equity flows slowed dramatically. The Nigeria stock exchange, for example, fell by 46%, becoming the world's worst performing market.

Several recent studies have examined how news shocks from one international stock market influence the volatility process of other markets. Accordingly, stock market returns are vulnerable to both rising and falling swings. Empirical work has documented patterns in the vulnerability of countries to volatility and identified possible channels through which shocks are transmitted.

Trade links, regional patterns, and macroeconomic similarities make countries vulnerable to volatility (Dornbusch and Claessens, 2000). Furthermore, loosening capital controls between markets, advancing computer technology, and faster processing of worldwide news have enhanced the volatility process (Booth *et al.*, 1997).

Volatility spillover, also known as contagion, usually results from the interdependence among market economies. This interdependence means that shocks, whether of global or local nature, can be transmitted across countries because of their financial linkages. That is, volatility spillover or contagion refers to the spread of market disturbances from one country to another, a process observed through co-movements in stock prices, exchange rates, or capital flows (Dornbusch and Claessens, 2000). Financial contagion can create financial volatility and can seriously damage the economy and financial systems of countries. There are several branches of classifications that explain the mechanism of financial contagion, which are spillover effects and financial crisis that are caused by the influence of the four agents' behavior. The four agents that influence financial globalization are governments, financial institutions, investors, and borrowers.

Modelling and forecasting volatility and correlations are now at the heart of financial econometrics as accurate estimates of volatility and correlation are required in derivative pricing, portfolio optimization, risk management and hedging strategies (Sadorsky, 2012).

Although the idea that financial markets do influence each other had been well understand (see Engle, Ito, & Lin, 1990; Koutmos, 1996), the growing integration of financial markets has led to renewed interest on stock market interaction and the mechanisms by which stock return movements are transmitted . For example(Guimar~aes-Filho & Hong, 2016 and Tsutsui & Hirayama, 2013 analyses the interaction between Japanese, Korean and Chinese stock markets using volatility and correlation models). Yang, Hsiao, and Wang (2006) examine EM crisis and stock market linkages using vector autoregressive (VAR) models while Salisu and Oloko (2015b) investigate spillover effects between stock and foreign-exchange (FX) markets in Nigeria using a variant of BEKK-vector autoregressive moving average asymmetric-MGARCH (BEKK-VARMA-AMGARCH) model of McAleer, Hoti, & Chan, 2009. In addition, Hassanand Malik (2007) investigated the transmission of volatility among different US sector indices with

EMs, while Miralles-Marcelo *et al.* (2013) examine volatility relations among Spanish firms using MGARCH models.

Iryna Kharchenko and Plamen Tzvetkov (2013) examine the effect and levels of volatility contagion between several stock indices. By using three developed and three developing indices, they form a hypothesis that spillovers are transferred from the developed to the developing markets. Their subsample after the financial crisis yields considerably different outcomes. The only spillover occurs between the developed markets and India, implying that there were weaker dependencies between the developed and emerging economies. This finding shows that post financial crisis has lead to diminishing interdependencies of Russia and China on the developed markets, while raising the significance of developed countries on India.

Some researchers choose BEKK such as Tastan (2006) to model time-varying correlation. However, the large number of parameters needing to be estimated for the high dimension general form has been emphasized and the exact interpretation and impact of the individual coefficients is difficult to discern and interpret (Sheppard, 2003). There is another strand of interesting study and correspondingly empirical studies using Enlge (2002) dynamic conditional correlation model (DCC) which is a generous model allowing for time-varying correlation as well as for the plausibility of estimation. Lee (2006) employs the DCC model to document the fact that the overall price level tended to move in the same direction as output in the periods before the World War II but in the opposite direction after the war. Aslanidis, Osborn and Sensier (2008) provide evidence on the source of co-movement in monthly US and UK stock returns by investigating the role of macroeconomic and financial variables with the DCC and related modified DCC models. Besides, Vector Autoregressive (VAR) lags method is applied to capture return spillover and the interdependence of one market on another.

1.2 Statement of the Problem

In recent years, stock markets in the world have been exhibiting increase interdependence. Due to advances in information technology, financial globalization, in there, stock market's volatility could easily spillovers from one market to another.

Volatility is a measure of uncertainty about future asset price or return change. It is a significant input in risk management, strategic financial planning and policy modelling. Financial contagion can create financial volatility and can seriously damage the economy and financial systems of countries.

There are several studies focusing on the stock market linkage across countries. For instance, Kim and Rogers (1995), Surya (2009), Sariannidis *et al* (2010),Soultanaeva(2011).
However, there is a dearth of work, focusing on volatility spillover/contagion between developed stock markets and African stock markets. This thesis attempts to fill this important gap in the literature. In particular the following research questions are addressed.

1. Are there volatility spillovers from developed stock markets to African stock markets?
2. Does volatility spillovers increasing over time from developed stock markets to African stock markets?
3. Which of the African countries under consideration shows stronger integration with developed countries' stock markets?

In order to answer these questions, this thesis models volatility spillovers/contagion from developed to selected African stock markets using MGARCH models. As will be explained in section 3, weekly closing data from developed, Africa and USD stock markets are used to answer these questions within an MGARCH modeling framework.

1.3 Objectives of the Study

1.3.1 General Objective

The main objective of this study is modelling volatility spillovers/contagion from developed stock markets to selected African stock markets using MGARCH model.

1.3.2 Specific Objectives

The following are the specific objectives addressed in this study. Those are:

- To estimate volatility spillovers effect from developed to selected African stock markets.
- To determine the magnitude and trend of volatility spillovers.
- To determine which MGARCH model fits the conditional covariance better.
- To compare the degree/level of correlation/contagion amongst considered African stock markets.

1.4 Significance of the Study

This study will be relevant for policy makers, investors, governments, financial institutions, traders and borrowers regarding to their responsibility, since such bodies are accountable for volatility spillovers in the stock markets and to formulate policies, strategies and plans to reduce the risk that African countries would have in the future.

The finding of this thesis helps investors to have better understand regarding to volatility spillovers of stock markets in Africa and the risk that they should be considered to maximize their gain. The results of this thesis is used as literature for further studies related to volatility spillovers in the world`s stock market using MGARCH model.

It is also hoped that African countries such as Ethiopia who are yet to have stock market will find the present work useful as it is based on countries with similar level of development.

1.5 Organization of the Study

This thesis was organized into the following sections. Section one is introduction of the thesis. This section briefly addresses the thesis objectives, significance, and background of the study.

Section 2 reviews the literature with emphasis on the statistical tools relevant to modeling the volatility spillover/contagion from developed to African stock markets. Section 3 explains the methodology which has been applied in building VAR and MGARCH models and estimating their parameters. Section 4 presents the results of analysis. Section 5 concludes the results.

2. LITERATURE REVIEW

2.1 Theoretical Literature

Volatility is a measure of uncertainty about future price or return changes on assets. Regarding to the factors which drive volatility, there are two arguments. Some scholars say it is exogenously driven by unobservable factor which is correlated with the asset returns. But others concluded that stock market volatility has a very strong pattern of business cycle. According to Jones volatility will be higher during recession than during expansion (Jones P C, 2002). Economists and policy makers have largely believe financial globalization has the primary impact of reducing domestic barriers to cross-border financial flows. This move towards free and fast capital flow results in all the countries within a global market making closely related and dependent up on each other, therefore, a financial crisis in one country can quickly spread to other countries (Dymski, 2005). However, in this study we investigated volatility spillovers among developed stock market to selected African stock markets.

Financial contagion can create financial volatility and can seriously damage the economy and financial systems of countries. There are several branches of classifications that explain the mechanism of financial contagion, which are spillover effects and financial crisis that are caused by the influence of the four agents' behavior. The four agents that influence financial globalization are governments, financial institutions, investors, and borrowers.

The first branch, spill-over effects, can be seen as the negative externalities. Spillover effects are also known as fundamental-based contagion. These effects can happen either globally, heavily affecting many countries in the world, or regionally, affecting only neighboring countries. The big players, who are more of the larger countries, usually have a global effect. The smaller countries are the players who usually have a regional effect. These forms of co-movements would not normally constitute contagion, but if they occur during a period of crisis and their effect is adverse, they may be expressed as contagion Dornbusch, Rudiger; Park, Yung; Claessens, Stijn (2000).

Fundamental causes of contagion include macroeconomic shocks that have repercussions on an international scale and local shocks transmitted through trade links, competitive devaluations, and financial links. It can lead to some co-movements in capital flows and asset prices. Common

shocks can be similar to the effects of financial links. A financial crisis in one country can lead to direct financial effects, including reductions in trade credits, foreign direct investment, and other capital flows abroad. Financial links come from financial globalization since countries try to be more economically integrated with global financial markets. Alen and Gale (2000),and Lagunoff and Schreft (2001) analyze financial contagion as a result of linkages among financial intermediaries. The former provide a general equilibrium model to explain a small liquidity preference shock in one region can spread by contagion throughout the economy and the possibility of contagion depends strongly on the completeness of the structure of interregional claims. The latter proposed a dynamic stochastic game-theoretic model of financial fragility, through which they explain interrelated portfolios and payment commitments forge financial linkages among agents and thus make two related types of the financial crisis can occur in response.

Trade links is another type of shock that has its similarities to common shocks and financial links. These types of shocks are more focused on its integration causing local impacts. Any major trading partner of a country in which a financial crisis has induced a sharp current depreciation could experience declining asset prices and large capital outflows or could become the target of a speculative attack as investors anticipate a decline in exports to the crisis country and hence a deterioration in the trade account. Kaminsky and Reinhart (2000) document the evidence that trade links in goods and services and exposure to a common creditor can explain earlier crises clusters, not only the debt crisis of the early 1980s and 1990s, but also the observed historical pattern of contagion.

Competitive devaluation is also associated with financial contagion. Competitive devaluation, which is also known as a currency war, is when multiple countries compete against one another to gain a competitive advantage by having low exchange rates for their currency. Devaluation in a country hit by a crisis reduces the export competitiveness of the countries with which it competes in third markets, putting pressure on the currencies of other countries; especially when those currencies do not float freely. This action causes countries to act irrationally due to fear and doubt. If market participants expect that a currency crisis will lead to a game of competitive devaluation, they will naturally sell their holdings of securities of other countries, curtail their lending, or refuse to roll over short-term loans to borrowers in those countries.

Another branch of contagion is a financial crisis, which is also referred to irrational phenomena. A financial crisis as a branch of contagion is formed when a co-movement occurs, even when there are no global shocks and interdependence and fundamentals are not factors. It is caused by any of the four agents' behaviors who influence financial globalization. Some examples that can cause contagion are increased risk aversion, lack of confidence, and financial fears. Under the correlated information channel, price changes in one market are perceived as having implications for the values of assets in other markets, causing their prices to change as well (King and Wadhwani (1990)). Also, Calvo (1999) argues for correlated liquidity shock channel meaning that when some market participants need to liquidate and withdraw some of their assets to obtain cash, perhaps after experiencing an unexpected loss in another country and need to restore capital adequacy ratios. This behavior will effectively transmit the shock.

Out of the four agents, an investor's behavior seems to be one of the biggest one that can impact a country's financial system. There are three different types of investor behaviors, which generally are considered rational or irrational and individually or collectively.

The first type of behavior is when investors take action that is ex-ante individually rational but lead to excessive co-movements – excessive in the sense that they cannot be explained by real fundamentals. It breaks down into two sub-categories, liquidity and incentive problems and information asymmetries and coordination problems. The first sub-category is liquidity and incentive problems. A reduction of equity prices can result in a loss of money for investors. These losses may induce investors to sell off securities in other markets to raise cash in anticipation of a higher frequency of redemptions. These liquidity problems are also challenges for banks, specifically commercial banks. Incentive problems can also have the same effects as liquidity problems. For instance, the first signs of a crisis may cause investors to sell their holdings in some countries, resulting in equity and different asset markets in economies to decline in value. This causes the value of currencies in these economies to also decrease. The second sub-category is information asymmetries and coordination problems. This type of investor behavior can either be considered rational or irrational. This sub-category is when one group, or country, has more or significantly better information compared to another group or country. This can cause a market failure problem, which could potentially cause a financial crisis.

The second type of investor behavior concentrates on multiple equilibriums. It focuses on the investor's behavioral changes when the financial market can have multiple equilibrium changes. Thus, contagion occurs when a crisis in one financial market causes another financial market to move or jump to a bad equilibrium, characterized by devaluation, a drop in asset prices, capital outflows, or debt default.

The third type of behavior is when there is a change in the international financial system, or in the rules of the game. It can make investors adjust their behaviors after a financial transaction occurs internationally or an initial crisis occurs. These behaviors can lead to spillover effect, causing contagion.

In addition, there are some less-developed explanations for financial contagion. Some explanations for financial contagion, especially after the Russian default in 1998, are based on changes in investor "psychology", "attitude", and "behavior". This stream of research date back to early studies of crowd psychology of Mackay (1841) and classical early models of disease diffusion were applied to financial markets by Shiller (1984). Also, Kirman (1993) analyses a simple model of influence that is motivated by the foraging behavior of ants, but applicable, he argues, to the behavior of stock market investors. Faced with a choice between two identical piles of food, ants switch periodically from one pile to the other.

2.1.1 Financial Globalization

Financial globalization is implied as the integration of a country’s local financial system with international financial market. According to Schmukler, integration takes place when liberalized economies experience an increase in cross-country capital movement, including an active participation of local borrowers and lenders in international markets and a widespread use of international financial intermediaries (Schmukler, 2004).

Frenkel describe financial globalization as a historical process with two dimensions. One is the growing volume of cross border financial transactions; the other is the sequence of institutional and legal reforms implemented to liberalize and deregulate international capital movements and national financial systems (Frenkel, 2003).

Financial globalization is not a new phenomenon it was existed for a long time. However, a hundred years ago only a few countries and sectors were participated in the process of capital flow which directed toward supporting trade flows. The appearance of the First World War followed by the Great Depression and Second World War forced governments to impose control on capital flows to regain monetary policy independence (Bordo, 2000).

2.1.2 Features of Financial Time Series Data

In empirical economic analysis, observations on a variable may be available on once a year or once a quarter and thus come from repeated observations, corresponding to different dates. The sequence of these observations on one variable is called time series (Gourieroux and Monfort, 1990 pp 1). Financial time series is concerned with a sequence of observations on financial data obtained in a fixed period of time. According to Tsay financial time series data analysis is differ from other time series analysis because the financial theory and its empirical time series contain an element of complex dynamic system with a high volatility and a great amount of noise (Tsay, 2005 pp 1). The uncertainty and noise makes the series to exhibit some statistical regularity, which are known as stylized facts. Stylized facts are empirical observations that are so consistence and have been made in so many contexts that they are accepted as truth. Stylized facts are obtained by taking a common denominator among the properties observed in studies of different markets and instruments (Cont R, 2000).

Therefore most financial data exhibits features like:

Volatility clustering: - Volatility does not keep constant. It is quite common that large returns tend to be followed by large returns and small returns tend to be close with low returns.

Leptokurtosis effect: - By viewing the value of kurtosis, we 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.

Leverage effect: - Volatility is higher after negative shocks than after positive shocks of same magnitude.

S**kewness**: - The effect of skewness may be positive or negative, which describes their departure from symmetry.

Long-range dependence in the data: - Sample autocorrelations of the data are small whereas the sample autocorrelations of the absolute and squared values are significantly different from zero even for large lags. This behavior suggests that there is some kind of long-range dependence in the data

Long-run memory effect: - The existence of this effect reflects persistence temporal dependence even between distant observations.

There are many empirical studies that show the existence of co-movements and interdependence between capital markets in the global market. Such co-movement can create interaction between the volatility of different financial market which we can call it volatility spillover. Volatility spillover may exist between the markets of different geographical locations and also between different types of financial markets, such as between the stock markets, the foreign exchange markets and the bond markets (Mulyadi, 2009).

Mulyadi on his work "volatility spillover in Indonesia, USA and Japan capital market" use two terminologies when he explain the nature of volatility spillover, contemporaneous volatility spillover and dynamic volatility spillover. According to him, Contemporaneous volatility spillover is volatility spillover in the very same day which could generally happen on stock markets in a same region having overlapping trading time. So, information between markets could be transmitted on the same day where trading still take place. Based on this information, investor could make a decision that will impact that capital market. Meanwhile, volatility spillover that could happen between capital markets in different region is called dynamic volatility spillover. Time-trading difference is attributed from starting and closing time of trading. One capital market starts trading when the other has been closed or almost in closing time of trading. Therefore, information from one capital market will made an impact to the other on next trading day, so volatility spillover happen on the next day (Mulyadi, 2009).

2.2 Empirical Literature

The recent financial and credit crises have shifted focus on the interdependence level of financial markets, as well as volatility spillovers (Gatfaoui, 2012). International stock markets, under ever expanding globalization, have been experiencing an increasing interdependency or interaction with one another as a result of information spillovers among stock markets. Morana and Beltratti

(2008) reveal the increasing co-movements of prices, returns, volatilities and correlations between the developed markets of the USA, UK, Germany and Japan. Understanding these links is very important for determining asset allocations, pricing domestic securities, implementing global hedging strategies, (Ng, 2000). Gunasinghe (2005) concluded that the Indian stock market had a low volatility spillover effect on other regional markets, like Sri Lanka and Pakistan. Abraham and Seyyed (2006) found an asymmetric volatility spillover from the more accessible, but smaller, Bahirini market to the less accessible Saudi market. The existence of volatility spillovers implies that one large shock increases the volatilities not only in its own asset or market, but also in other assets or markets as well. Volatility and its changes signal the flow and arrival of new information (Ross, 1989). If information comes in clusters, asset returns or prices may exhibit volatility even if the market perfectly and instantaneously adjusts to the news. Thus, study on volatility spillover can help understanding how information is transmitted across equity markets. As a consequence, current literature has increasingly focused on the spillover effect and volatility (Like Kim, 2009; Beirne, *et.al*. 2010; Mukherjee and Mishra, 2010; Park, *et.al*., 2010; Kumar and Pandey, 2011 among others). An important issue in asset allocation and risk management is whether financial markets become more interdependent during financial crises. This issue has acquired great importance among academics and practitioners, especially since the appearance of several emerging market crises of the 1990s (Kenourgios and Padhi, 2012). Until then, financial crises models were developed with regard to crises as events occurring in individual countries. However, those crises episodes focused the empirical research on the examination of contagion effects and the inter-regional or intercontinental nature of the shocks. The main concern is to choose a reliable and consistent volatility measure. The volatility of financial markets represents the magnitude of the movement between the current and previous returns. The error terms (also referred to as residuals or innovations) illustrate the uncertainty over time and represent the risk measure in the financial markets. Kyle (1985) suggests that volatility of stock prices contains more information than the actual price. Since volatility is a time-varying risk measure (volatility clustering effects of large (small) changes followed by other large (small) changes) the relationship of the stock indices movements across the markets allows for estimation of conditional variance that is present in time-series data (Mukherjee and Mishra, 2010). Chuang *et al*. (2007) found significant interdependence among the conditional variance of six East Asian markets when studying volatility transmissions. They conclude that

Japan is the most influential market in their study group, which is also supported by Gebka and Serwa (2007). Time-variation in the conditional variance of financial time-series is also important when attempting to calculate risk and other hedging strategies (Hansen and Lunde, 2001).

2.2.1 Empirical Findings on Volatility Spillovers

The above findings clearly indicate that volatility spillover contributes a significant effect on interdependent markets. This explains the increasing studies toward identifying any trends and directional volatility transmissions. However, most of these studies seem to focus on the impact between developed markets, or alternatively between local and regional markets. This research, was try to establish any potential volatility spillovers specifically from developed to selected African stock markets and identify the directional co-movements of the volatility.

Researchers have conducted studies on volatility spillover between the US and other emerging markets and determined a unidirectional transmission of volatility from the US to the other countries (Kumar and Pundey, 2011). This finding appears quite intuitive and supports my hypothesis. Al-Zeaud and Alshbiel (2012) state that researchers have examined volatility spillovers between mature and emerging markets and determined that mature markets do indeed influence the conditional variances and returns of other regional markets. Chittedi (2007) used a Granger Causality test and concluded that the developed markets of the US, Japan and France have an influence on the developing market of India. However there was no evidence that the developed markets had an effect on the other Brazil, Russia, and India and China (BRIC) nations. Kenourgious (2007) examined the relationships between the developed markets of the US and UK with the emerging BRIC markets and found an increase in the correlations and volatilities during crisis periods as opposed to stable times. Bhar and Nikolova (2009) analyzed the interaction of the BRIC nations with the rest of the world. Their research concludes that India exhibits the highest regional and global interdependence, followed by Brazil, Russia and lastly China. To my knowledge there are no other researches that extensively focus on spillover contagion from the developed to the African stock markets. Therefore, this thesis focuses on contributing further findings of volatility linkages precisely between those two specific groups.

2.2.2 Conditional Variance Models

Many researches on volatility spillovers has stirred an enormous interest amongst researchers and practitioners to develop models that can accurately estimate and forecast volatility. To capture the time-varying feature of conditional correlation between equities and exchange rates, Tong (1996) adopted the BEKK multivariate GARCH model. The BEKK algorithm permits time variation in the conditional covariance while it ensures the condition of a positive-definite, variance covariance matrix. But as for many currency markets, Sheedy (1998) found that the BEKK specifications would not be effective in eliminating the correlation structure. Siu Pang Au-Yeung and Gerard Gannon (2002) applied BEKK-GARCH model with multiple switch points in the variance equations and they found to capture the structural changes that have taken place in the Hong Kong markets. They found the BEKK-GARCH (1,1) model with 3 switching points was superior to other models with less switching points. It was able to capture structural changes in the volatility structure. Hence, their results showed there are significant impacts on the informational efficiency in the stock and futures market following the policy changes. Kroner and Sultan (1991) applied the constant-correlation bivariate GARCH (bivariate CCC-GARCH) model to hedge the currency exposure risk. While conditional variance of different assets and currency forward prices changes over time, the conditional correlations for currency markets are assumed to be constant in order to get a positive definite variance-covariance matrix as proposed in Bollerslev (1990). This constant-correlation approach has been widely applied because of its computational simplicity. But the financial data of equities and exchange rates provided strong evidence that the assumption of having a constant correlation was violated for these markets. Luc Bauwens and Sebastien Laurent (2004) showed that a high dimensional VaR problem could be solved without imposing strong restrictions on both the covariance structure and the distribution of the innovations. They showed that new family of distributions (the multivariate skew-Student density) combined with a multivariate DCC-GARCH model is useful for modeling financial returns and forecasting the Value-at-Risk (VaR) of portfolios of assets. Indeed, they found that the multivariate skew Student density provides better, or at least not worse, out-of-sample VaR forecasts than a symmetric density. Robert Engle (2002) showed in his paper that the bivariate version of DCC model provides a very good approximation to a variety of time varying correlation processes. The comparison of DCC with simple multivariate GARCH and several other estimators showed that the DCC is often the most accurate. This is true whether the

criterion is mean absolute error, diagnostic tests or tests based on value at risk calculations. Empirical examples from typical financial applications are quite encouraging as they reveal important time varying features that might otherwise be difficult to quantify. Statistical tests on real data indicated that all of tested models are misspecified but that the DCC models are competitive with the multivariate GARCH specifications and superior to moving average methods. Shohreh Valiani (2004) adopted MGARCH specification that has been applied to estimate the time varying correlations of underlying assets and related currency forwards in order to hedge the currency exposure risk in an international portfolio context. The empirical investigation shows that the optimal multivariate GARCH dynamic hedging strategy can capture the currency fluctuations the best and over-performs the risk controlling procedure. John Elder (2003) derived an analytical expression for an impulse-response function for a vector autoregression with multivariate GARCH errors, where the vector of conditional means is a function of the conditional variances. He also provided the appropriate interpretation of an impulse-response function for such models and suggests interesting empirical issues that can be addressed within this framework. Extending the constant-correlation model to allow for time-varying correlations provided some interesting empirical results. In particular, the estimated conditional-correlation path provides an interesting time history that would not be available in a constant-correlation model. Tim Bollerslev (1989) proposed a multivariate time series model with time varying conditional variances and covariances, but constant conditional correlations (CCC model). Parametrizing each of the conditional variances as a univariate GARCH process, the descriptive validity of the model was illustrated for a set of five nominal European U.S. dollar exchange rates following the inception of the European Monetary System (EMS). When compared to the pre-EMS free float period, the co-movements between the currencies were found to be significantly higher over the later period.

The correlations measured the linear relationships between the residuals of the GARCH-models and as these residuals mainly reflect bank specific factors they are suitable to quantify the systemic risk. Thus, in order to investigate volatility spillovers/contagion from developed to selected African stock markets multivariate GARCH model representation will be used.

3. DATA AND METHODOLOGY

3.1 Source of Data

This study used stock market data obtained from Bloomberg and span for the period of 1999 week 1 to 2017 week 46. The data have information about the US dollar denominated weekly closing stock indices, developed weekly closing indices, African weekly closing indices and **weekly stock returns** are defined as 100 times the first differences of the log stock indices. The total number of observation for each stock market was 983.

3.1.1Four selected African stock market indices

The four African stock markets are selected based on the information in the past which gave very high return in the world and there were in 10-top best performing countries in the world since 1995 as explained in section one.

Kenya stock indices

The Nairobi Securities Exchange Ltd 20 Share Index is a price weight index. The members are selected based on a weighted market performance for a 12 month period as follows: Market Capitalization 40%, Shares Traded 30%, Number of deals 20%, and Turnover 10%.

Morocco stock indices

The MASI index is a broad based free float index comprising all shares listed on the Casablanca Stock Exchange.

South African stock indices

The JSE Africa All Shares Index is a market capitalization-weighted index. Companies included in this index make up the top 99% of the total pre free-float market capitalization of all listed companies on the Johannesburg Stock Exchange

Nigerian stock indices

The Nigerian Stock Exchange all Share Index was formulated in January 1984 with a base value of 100. Only ordinary shares are included in the computation of the index.

3.1.2Two Developed market and one currency indices

Standard and Poor's 500 Index is a capitalization-weighted index of 500 stocks. The index is designed to measure performance of the broad domestic economy through changes in the aggregate market value of 500 stocks representing all major industries.

The S&P Europe 350 Index is a free float market cap weighted index that measures the performance of equities in 17 Pan-European markets, covering approximately 70% of the total market cap. It offers an effective balance between broad market representation and liquidity. The **U.S. Dollar Index** (USDX) is an index of the value of the United States dollar relative to a basket of foreign currencies, USDX started in March 1973, soon after the dismantling of the Bretton Woods system.

3.2 Study Variables

3.2.1 Dependent Variable

The endogenous (response) variable were weekly closing stock markets returns (r_{it}) of developed and selected African stock markets. Where t=week1 1999, week 2 1999 … week 46 2017 and i=1, 2, 3 represents the stock markets for developed, selected African and US dollar return respectively.

3.2.2 Independent Variables

The independent variable for this study were the lagged values of weekly closing returns for the mean model, while lagged volatility in the stock markets was used as independent variable in the covariance model .

3.3 METHODOLOGY

3.3.1 Descriptive Data analysis

In this study the following descriptive statistics are used. Those are minimum, maximum, mean, standard deviation, skewness, kurtosis, and graph.

3.3.2 Inferential Statistics

3.3.2.1Definition of time series data

Time series is broadly classified in to two major parts: univariate and multivariate time series. Univariate time series uses only the past history of the time series being forecast plus current and past random error terms. ARIMA modeling is a specific subset of univariate modeling in which a time series is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of a 'white noise' error term (the moving average component).Multivariate time series involves a vector of time series data that will be modeled simultaneously.

3.3.2.2 Stochastic process

A stochastic process is a series of time indexed random variables $Y(g,t)$, where g belongs to a sample space and t to an index set. For a fixed set $t, Y(g,t)$ is a random variable; for a given $g, Y(g,t)$ as a function of t is called a realization. The population that consists of all possible realizations is called the enstimble in stochastic process and time series analysis. Thus, a time series is a realization or sample function from a certain stochastic process (William, 2006).

3.3.2.3 Stationarity

A stationary process has the property that the first and second moments do not change over time. It is an essential property to define a time series process. Stationarity may be weak or strong.

Weak Stationarity

A stochastic process $\{Y_t\}$ is said to be weakly stationary or covariance stationary if the mean of Y_t, the variance of $Y_t$and the covariance betweenY_t and Y_{t+k} are time invariant, where$k$ is an arbitrary integer.

If one of these properties or characteristics violated the time series process $\{Y_t\}$ is non stationary and we have to handle it by appling differencing for appropriate number of times or other methods.

Strong (Strict) Stationarity

A time series is said to be strictly stationary if its properties are not affected by a change in the time origin. That is, if the joint probability distribution associated with n observations $\{Y_1, Y_2 \ldots Y_n\}$made at any set of times $t_1, t_2 \ldots t_n$ is exactly the same as the joint probability distribution

of the observations$\{Y_{t1}, Y_{t2} \ldots Y_{tn}\}$made at times $t_{1+k}, t_{2+k} \ldots t_{n+k}$. Mathematically it can be expressed as:

F ($Y_{t1} \leq \tau_1$, $Y_{t2} \leq \tau_2$,… $Y_{tn} \leq \tau_n$) = F ($Y_{t1+k} \leq \tau_1$, $Y_{t2+k} \leq \tau_2$, $Y_{tn+k} \leq \tau_n$) ……. [3.1]

Therefore weak (covariance) stationarity does not mean that strong or strict stationarity.

Many financial time series appear to be non-stationary.

The first step for an appropriate analysis is to determine whether the time series is stationary or not. Due to non-stationarity, regressions with time series data are very likely to result in spurious results.

3.3.2.4 Stationarity Test (Unit root test)

Many economic and financial time series exhibit a trending behavior or non stationarity in the mean**.** Trivially, a non-stationary process arises when one of the conditions for stationarity does not hold. For non- stationary series, the effect of a shock never dies away. Moreover, a regression involving non-stationary variables leads to spurious regression; that is, one can regress completely unrelated series and find high R^2(indicating how well one term is at predicting another) and the standard tests are not valid (Granger and Newbold, 1986). A test for stationarity that has become widely popular over the past several years is the unit root test. Thus, the first step for an appropriate analysis is to determine whether the series is stationary or not.

Consider a random walk (AR (1)) process with drift:

Y_t= μ +$\phi_1 Y_{t-1}$ + ε_t ……[3.2]

Where $\varepsilon_t is$ a white noise process. Unit root tests are based on testing the null hypothesis that

$H_0 : \phi_1$= 1 (the series is not stationary) against

$H_0 : \phi_1$ <1 (the series is stationary)

They are called unit root tests because, under the null hypothesis, the characteristic polynomial has a root equal to unity. There are several unit root tests. But the most widely used ones are Augmented Dickey- Fuller (ADF) test due to Dickey and Fuller (1979), and the Phillip-Perron (PP) test due to Phillips (1986) and Phillips and Perron (1988).

3.3.2.5 Augmented Dickey-fuller (ADF) Unit Root Test

The ADF test is used to tests whether a unit root is present in an autoregressive model or not. It is developed by the statisticians David Dickey and Wayne Fuller in 1979. In its simplest form it considers an autoregressive of order one process with drift given by:

$Y_t = \mu + \phi_1 Y_{t-1} + \varepsilon_t$ ..... [3.3]

Where Y_t is the variable of interest and ε_t are the error term which is assumed white noise. If a unit root is present (if $\phi_1 = 1$), then the model would be non-stationary and stationary if absolute value of ϕ_1 less than one. We must have to use first difference to make it stationary, meaning that subtracting Y_{t-1} from both sides and the resulting regression model can be written as:

$\nabla Y_t = \mu + (\phi_1 - 1)Y_{t-1} + U_t = \mu + \Pi Y_{t-1} + \varepsilon_t$ .....[3.4]

Where $\Pi = \phi_1 - 1$ and therefore, the null hypothesis of the above unit root test is equivalent to:

$H_o : \Pi = 0$ (The series is not stationary) against

$H_1 : \Pi < 0$ (The series is stationary)

The test statistics is given by: $t = \frac{\hat{\Pi}}{se(\hat{\Pi})}$ ..... [3.5]

Where $\hat{\Pi}$ is the OLS estimator of Π and se ($\hat{\Pi}$) is the standard error of Π.

Dickey and Fuller (1979) showed that, under the null hypothesis of a unit root the test statistic given by (3.5) does not follow the conventional student's t-distribution and they derived asymptotic results and simulated critical values for various tests and sample sizes. MacKinnon (1991, 1996) implemented a much larger set of simulations than those tabulated by Dickey and Fuller.

The ADF test constructs a parametric correction for higher-order correlation by assuming that the series follows an AR (p) process and adding lagged difference terms of the dependent variable to the right-hand side of the test regression:

$\nabla Y_t = \Pi Y_{t-1} + \beta_1 \nabla Y_{t-1} + \cdots + \beta_p \nabla Y_{t-p} + U_t$ .....[3.6]

This augmented specification is then used to test for unit root using the t-ratio. An important result obtained by Dickey-Fuller (1979) is that the asymptotic distribution of the statistic is independent of the number of lagged first differences included in the ADF regression

3.3.2.6 Phillips and Perron (PP) Unit Root Tests

The statistic proposed by Phillips and Perron (1988) arise from their considerations of the limiting distributions of the various Dickey-Fuller statistics when the assumption that an iid process is relaxed. The test regression in the Phillips-Perron test is given by:

$Y_t = \alpha + \beta t + \Pi Y_{t-1} + U_t$ ……[3.7]

Where U_t is a stationary process (which may be heteroscedastic). The PP test corrects for any serial correlation and heteroscedasticity in the errors of the test regression by directly modifying the Dickey-Fuller test statistic. The modified statistics, denoted by $Z_t \; and \; Z_\Pi$, are given by:

$Z_t = (\frac{\hat{\sigma}^2}{\hat{\lambda}^2})^{1/2} - \frac{1}{2}\left(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}\right)\left(\frac{T\,se((\hat{\Pi})}{\hat{\sigma}^2}\right)$ …….. [3.8]

$Z_\Pi = T\,\Pi - \frac{1}{2}\left(T^2\,\frac{se((\hat{\Pi})}{\hat{\sigma}^2}\right)(\hat{\lambda}^2 - \hat{\sigma}^2)$. …….. [3.9]

The terms $\hat{\lambda}^2$ and $\hat{\sigma}^2$ are the variance parameters that are given by:

$\hat{\sigma}^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E(U_t{}^2)$ ……... [3.10]

$\hat{\lambda}^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E(S_t{}^2)$ Where $S_t{}^2 = \sum_{t=1}^{T} U_t$ ……[3.11]

Under the null hypothesis that $H_0 : \Pi = 0$, the statistics $Z_t \; and \; Z_\Pi$ have the same asymptotic distribution as the ADF t-statistic.

3.3.2.7 Granger Causality Tests

These tests were introduced by Granger back in 1969, slightly altered by Sims in 1972, and establish whether changes in one variable cause changes in another variable. Mathematically speaking if y_1 causes y_2, then the lags of y_1 should have a significant weight when defining changes in y_2 variable, in other words we can state that y_1 "Granger-Causes" y_2 or that we established univariate causality. If both lag of y_1 and y_2 were significant then we could say that there is a bi-directional causality. If the relationship is unidirectional, then we can say that the variable that causes the changes is strongly exogenous in the equation.

In this case this thesis examined the relationship between stock indices in our study in order to determine the direction of return spillover. Granger causality test can be run only if both variables are stationarity.

3.4 Vector Autoregressive Model

The main purpose of this study is modelling volatility spillovers/ contagion from developed to selected African stock markets. However, before modeling the random variance (volatility) model it is necessary to model the mean model. Thus, vector autoregressive model is used to model the mean equations for each stock market's own returns and the returns of other markets lagged one period to analyze the existence of mean return spillover. Vector autoregressive (VAR) models are proposed by Sims (1980) and can be used to capture the dynamics and the interdependency of multivariate time series. It is regarded as a generalization of univariate autoregressive models or a combination between the simultaneous equations models and the univariate time series models. Let $Y_t = (y_{1t}, y_{2t},...,y_{nt})`$ denote an (n×1) vector of time series variables. The basic p-lag vector autoregressive (VAR (p)) model has the form:

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \ldots + \Pi_p Y_{t-p} + \varepsilon \ldots\ldots\ldots\

In this study a tri-variate VAR (p) model is applied for weekly closing stock market returns. For instance, tri-variate VAR (1) model has the form:

$$\begin{pmatrix} r_{1t} \\ r_{2t} \\ r_{3t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} + \begin{pmatrix} \pi_{11} & \pi_{12} & \pi_{13} \\ \pi_{21} & \pi_{22} & \pi_{23} \\ \pi_{31} & \pi_{32} & \pi_{33} \end{pmatrix} \begin{pmatrix} r_{1\,t-1} \\ r_{2\,t-1} \\ r_{3\,t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad [3.15]$$

Where, r_{it} is a 3x1 vector of weekly returns at time t for each stock market. In the above tri-variate VAR (1) model, (i=1, 2,3) represents the weekly developed stock returns, selected African stock return and US dollar return respectively. The diagonal elements π_{ii} of matrix π are the respective market's own returns lagged one period, while the off-diagonal elements π_{ij} represent the mean spillover effect across markets. The 3x1 vector c_i contains constants and 3x1 vector of ε_i is the disturbance term.

3.4.1 Lag Length Selection

The lag length for the VAR (p) model may be determined using model selection criteria. The general approach is to fit VAR (p) models with orders p =0,...,p max and choose the value of p which minimizes some model selection criteria. Model selection criteria for VAR (p) models have the form:

$$IC(p) = \ln|\textstyle\sum_p| + C_T \cdot \Theta(n.p) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\

The AIC criterion asymptotically overestimates the order with positive probability (not zero), whereas the BIC and HQ criteria estimate the order consistently under fairly general conditions if the true order p is less than or equal to p_{max}. For a model to be best it should have the smallest information criteria.

3.4.2 Parameter Estimation

In VAR model we assume that the error terms are uncorrelated with any of the lagged endogenous and exogenous variables. Thus, the usual OLS estimator could estimate the parameters efficiently and consistent for each stock market returns.

3.4.3 Model Adequacy Checking

After model selection and parameter estimation the next procedure is checking the adequacy of the model in order to use the model for some specific purpose (for example forecasting). If some key model assumptions seem to be violated, then a new model should be specified, fitted and checked again until the model is found that provides an adequate fit to the data.

Two types of tests for residual autocovariane are popular in applied work, Breusch-Godfrey LM tests and portmanteau tests. They are both based on statistics of the form:

$Q = TC' \sum^{-1} C$ ……. [3.20]

Where, Σ is a suitable scaling matrix. In other words, they are based on the residual auto covariance. The estimated of scaling matrix Σ determines the type of test statistic and its asymptotic distribution under the null hypothesis of no residual autocovariane.

3.4.3.1 Portmanteau Autocorrelation Test

Suppose $Y_t = (Y_{1t}, Y_{2t}. . . ., Y_{kt})'$ is k-dimensional vector of observable time series variables. From equation (3.20) the residual auto covariance is

$C_j = \frac{1}{T}\sum\sum_{t=1}^{T} \boldsymbol{\varepsilon_t \varepsilon_{t-j}}$ ……... [3.21]

The Portmanteau test for residual autocorrelation checks the null hypothesis that all residual auto covariance are zero, that is,

$H_o : E(\boldsymbol{\varepsilon_t \varepsilon_{t-j}}) = 0$ (i = 1, 2,3) …….. . [3.22]

Where $\boldsymbol{\varepsilon_t}$ are the estimated residuals. It is tested against the alternative that at least one auto covariance and, hence, one autocorrelation is nonzero. The test statistic is based on the residual auto covariance and has the form:

$Q_p = T\sum_{j=1}^{h} \mathrm{tr}(Cj'\Omega^{-1}Cj\Omega^{-1})$ ..... [3.23]

where

$C_j = \frac{1}{T}\sum \boldsymbol{\varepsilon_t \varepsilon_{t-j}}$ ..... [3.24]

$\Omega = \frac{1}{T}\sum \varepsilon_t \varepsilon'_t$ ..... [3.25]

The approximate distribution of this test statistic is the chi-squared distribution with k^2 (n-p) degrees of freedom in large samples if n is also large.

3.4.3.2 Autocorrelation LM Test

This test was developed by Breusch and Godfrey in 1978. Assume a VAR model for the error ε_t given by

$\varepsilon_t = \mathbf{D_1 U_{t-1} + \ldots + D_h U_{t-h}} + \upsilon_t$. ..... [3.26]

The quantity υ_t denotes a white nose error term. Thus, to test autocorrelation in υ_t we test

H0: $D_1 = \ldots = D_h = 0$ against

H1: $D_j \neq 0$ for at least one $j < h$.

The Lagrange Multiplier (LM) test for p^{th} order serial correlation is computed first by estimating an auxiliary regression where the OLS residuals are regressed on the variables in the original model plus p lagged residuals. The test statistic is either T times R^2 from the auxiliary regression or an F test that the coefficients on the lagged residuals are 0.

3.4.3.3 Multivariate Normality of the Residuals

Multivariate normality tests whether the residuals of the regression are multivariate normally distributed or not. The null hypothesis is that the residuals are multivariate normally distributed. Several tests for multivariate normality are available but the most commonly used test for multivariate normality of regression disturbances is due to Jarque and Bera (1980). The JB test statistic is:

$JB = T[a_1/6 + K^2/24]$ ..... [3.27]

Where, a_1 and k are the sample skewness and kurtosis coefficients, respectively.

This test statistic is asymptotically distributed as $\chi^2(2)$ under the null hypothesis; thus large values of this test statistic relative to the quantities from the $\chi^2(2)$ distribution lead to rejection of the null hypothesis.

3.5 Family of GARCH Models

Most financial time series such as asset return, option price and soon revels some structural facts like fat tails, existence of positive autocorrelation and leverage effect. And this cannot be captured by VAR models. Thus another model was introduced by Engle (1982) and Bollerslev (1986). Those are ARCH and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) family models respectively.

3.5.1 Autoregressive Conditionally Heteroskedasticity (ARCH) Model

One of the simplest volatility models is the autoregressive conditional heteroscedasticity (ARCH) model suggested by Engle (1982). ARCH models are the first attempt to capture the characteristics of financial time series without the assumption of constant variance for univariate time series. Consider Y_t denote a stationarity time series with conditional mean of ARMA family models. The error terms ε_t are split into a stochastic component $\eta_t$and a time dependent standard deviation $z_t$characterizing a typical size of the term given by:

$$\varepsilon_t = z_t\eta_t \quad \ldots\ldots [3.28]$$

To allow conditional heteroscedasticity, we assume that $var\ (\varepsilon_t|\theta_{t-1}) = E[(\varepsilon_t - \mu_t)^2|\theta_{t-1}] = {z_t}^2$, since $E\ ((\varepsilon_t|\theta_{t-1}) = 0$ where θ_{t-1} denotes the information set at time $(t-1)$. Here${z_t}^2$ denotes the variance conditional on the information set at time $(t-1)$ the mean model $\varepsilon_t = z_t\eta_t$,The ARCH (p, q) model is given by:

$$z_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 \ldots + \alpha_q\varepsilon_{t-q}^2 \quad \ldots\ldots [3.29]$$

${\varepsilon^2}_{t-1}$, ${\varepsilon^2}_{t-2}$ … are the lagged values of the squared innovation terms in the conditional mean equation of the series Y_t and we impose a non-negativity constraints $\alpha_0 > 0$and $\alpha_j \geq 0, j = 1, 2, \ldots, q$. the time varying volatility is captured by allowing volatility to depend on the lagged values of the squared innovation terms ${\varepsilon^2}_{t-j}$ and q is chosen such that the residuals of the

variance equation are white noise and $\{\eta_t\}$ is a sequence of independently and identically distributed random variables each with zero mean and unit variance. The term "Autoregressive" express that the process is depend on its past, the term "Conditional Heteroskedasticity" means the variance is time varying i.e. non constant variance Akgiray V. (1989. Bollerslev (1986) has extended the ARCH model in to the generalization of Engle's ARCH (GARCH) model by adding an autoregressive term to the moving averages of squared errors to capture the impact of lag conditional variance (Bollerslev, 1986).

Then the volatility process become GARCH (p, q) model is defined as:

$$z_t{}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{t-i} + \sum_{j=1}^{p} \beta_j z^2{}_{t-j} \quad \ldots\ldots\ldots\

3.5.2 GARCH (1, 1) models

The most frequently used GARCH model is the GARCH (1, 1) model. The equation of the conditional variance for GARCH (1, 1) is $z_t^2 = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta z^2_{t-1}$

3.5.3 ARCH/GARCH TEST

Before fitting GARCH class model it is necessary to check the presence of ARCH effect. This is commonly tested by Lagrange Multiplier and Ljung-Box.

3.5.3.1 Lagrange Multiplier (LM) Test for Serial Correlation

This test was developed by Breusch and Godfrey in 1978. This test is based on an AR representation of residuals and is used to test for serial correlation in the squared error terms. We first construct an auxiliary regression and estimate the sample residuals ε_t . Suppose that the residuals ε_t follow an autoregressive scheme given by:

$\varepsilon^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-2} + \ldots + \alpha_p \varepsilon^2_{t-p} + u_t$ ..... [3.31]

Where u_t is a white noise process and α_i 's are parameters of the model.

The Lagrange Multiplier (LM) test for order serial correlation is computed first by estimating the sample residuals ε_t (that is $\widehat{\varepsilon_t}$) by ordinary least squares (OLS) and regress the current residual $\widehat{\varepsilon_t}$ on the *p* lagged residuals. So, the fitted auxiliary regression model of residuals is given by:

$\hat{\varepsilon}_t = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1} + \alpha_2 \hat{\varepsilon}_{t-2} + \ldots + \alpha_p \hat{\varepsilon}_{t-m} \varepsilon_t$ .....[3.32]

The significance of the parameters α_i would indicate the presence of serial correlation under the null hypothesis.

Here the null hypothesis of absence of serial correlation up to lag p is: $H_0: \alpha_1 = \alpha_2 = \ldots = \alpha_m = 0$(there is no serial correlation among the residuals). If the usual R^2 statistic is computed for this model, the test statistic is:

$LM = TR^2$ .....[3.33]

And the distribution of the test statistic is:

$TR^2 \sim \chi^2(m)$ ..... [3.34]

Where, $R^2 is$ the coefficient of determination from the auxiliary regression and T is the sample size in the study.

3.5.3.2 Ljung-Box for serial correlation Test

The Ljung-Box (LB) test is one of the widely used lack-of-fit tests, that is, a test for the appropriateness of the fitted model. It was developed by Box and Pierce (1970) and modified by McLeod, et al. (1983). It is a statistical test which is used to test whether there is serial correlation in the squared residuals or not. Hence the null hypothesis of absence of serial correlation up to lag m is:

$H_0 : \rho_1 = \rho_2 = \cdots \rho_m$ (There is no serial correlation)

The test statistic is given by:

$$Q = T(T+2)\frac{\sum_{i=1}^{m} \hat{\rho}_i^{\,2}}{T-K} \quad \text{.....[3.35]}$$

Where, $\hat{\rho}_i$ is $i^{th} - lag$ sample autocorrelation of the residuals of the fitted model and T is the number of observations.

3.6 Multivariate GARCH Model

To analyze a volatility spillovers/contagion in the three markets we estimated a multivariate GARCH model which is the extension of univariate GARCH models. It helps to capture the dynamic relationship between developed stock markets and selected African stock markets. Multivariate GARCH models specify equations for how the variances and covariance move over time. Modeling a covariance matrix is difficult because of the likely high dimensionality 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. Obviously a disadvantage of the multivariate approach is that the number of parameters to be estimated in the GARCH equation increases rapidly, which limits the number of assets that can be included.

MGARCH models can be categorized in to four types (Silvennoinen and Teräsvirta, 2008):

• **Models of the conditional covariance matrix**: The conditional covariance is computed in a direct way. For example the vector error correction (VEC) and Baba-Engle-Kraft-Kroner (BEKK) models.

• **Factor models**: The return process is assumed to consist of a small number of unobservable heteroskedastic factors. This approach benefits from that the dimensionality of the problem reduces when the number of factors compared to the dimension of the return vector is small.

• **Models of conditional variances and correlations**: At first the univariate conditional variances and correlations are computed and then used to get the conditional covariance matrix. Some models are for example the Constant Conditional Correlations (CCC) model and the Dynamic Conditional Correlations (DCC) model.

• **Nonparametric and semi parametric approaches**: Models in this class form an alternative to parametric estimation of the conditional covariance structure. The advantage of these models is that they do not impose a particular structure (that can be misspecified) on the data.

Among many multivariate GARCH model CCC-GARCH and DCC-GARCH models are used in this study to modelling volatility spillovers.

The conditional covariance equation that are used in this thesis has the following form; consider first and second moments of returns in developed stock market, African stock markets and US dollar return using a tri-variate VAR-MGARCH (1,1) process. In its most general specification the model takes the following form:

$$R_t = \alpha + \beta R_{t-1} + \varepsilon_t \quad \ldots\ldots [3.36]$$

Where R_t= (developed stock markets return, selected African stock markets return and Us dollar returns), R_{t-1} is a corresponding vector of lagged returns, and ε_t= (ε_{1t} ε_{2t} ε_{3t}) is a residual vector. The residual vector ε_t is tri-variate and normally distributed $\varepsilon_t \,|\Theta_{t-1} \sim (0, H_t)$ with its corresponding conditional variance covariance matrix:

$$H_t = \begin{pmatrix} h_{11\,t} & h_{12\,t} & h_{13\,t} \\ h_{21\,t} & h_{22\,t} & h_{23\,t} \\ h_{31\,t} & h_{32\,t} & h_{33\,t} \end{pmatrix} \ldots\ldots\ldots\

3.6.3 Dynamic Conditional Correlations (DCC) models

The Dynamic Conditional Correlation model was proposed by Engle in 2002. It is a nonlinear combination of univariate GARCH models and it is also a generalized version of the CCC model. The number of parameters to be estimated is relatively smaller than the complete BEKK form with the same dimension when the number of stock market is small. When the number of stock market is large, the estimation of the DCC model can be performed by a two-step procedure which decreases the complexity of the estimation process. In brief, in the first place, the conditional variance is estimated via univariate GARCH model for each variable. The next step is to estimate the parameters for the conditional correlation. The DCC model can make the covariance matrix positive definite at any point in time. Two additional parameters, λ_1 and λ_2, are adjustment parameters that govern the evolution of the conditional quasicorrelations. They must be positive and sum to less than one. The sum of these parameters equal to zero tests the DCC model reduce to the special case of the CCC model. The magnitudes of the lambda parameters indicate that the evolution of the conditional covariance depends more on their past values than on lagged residuals' innovations. The form of Engle's DCC model is as follows:

$$H_t = D_t R_t D_t = \begin{pmatrix} \sigma_{1\,t} & 0 & 0 \\ 0 & \sigma_{2\,t} & 0 \\ 0 & 0 & \sigma_{3\,t} \end{pmatrix} \begin{pmatrix} 1 & \rho_{12\,t} & \rho_{13\,t} \\ \rho_{12\,t} & 1 & \rho_{23\,t} \\ \rho_{13\,t} & \rho_{23\,t} & 1 \end{pmatrix} \begin{pmatrix} \sigma_{1\,t} & 0 & 0 \\ 0 & \sigma_{2\,t} & 0 \\ 0 & 0 & \sigma_{3\,t} \end{pmatrix} \quad \text{..... [3.40]}$$

Where D_t is the standard deviation (volatility), D_t=diag($\sqrt{h_{11\,t}}$, ... , $\sqrt{h_{33\,t}}$) and R_t is is a 3x3 symmetric positive definite parameters matrix with unit diagonal elements. H_t has to be positive definite by the definition of the covariance matrix. Since H_t is a quadratic form based on R_t it follows from basics in linear algebra that R_t has to be positive definite to ensure that H_t is positive definite. Furthermore, by the definition of the conditional correlation matrix all the elements have to equal or less than one. To guarantee that both these requirements are met R_t is decomposed into

$R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{ diag}(Q_t)^{-1/2}$ where Q_t is a positive definite matrix defining the structure of the dynamics and $Q_t^{-1/2}$ rescales the elements in Q_t to ensure $q_{ij} < 1$.

$$Q_t = (1-\lambda_1-\lambda_2)R + \lambda_1 \widehat{\varepsilon_{t-1}}\ \widehat{\varepsilon_{t-1}} + \lambda_2 Q_{t-1} \quad \text{.....[3.41]}$$

A necessary condition to ensure the positivity of Q_t are non-negative scalar parameters of λ_1 and λ_2, satisfying $\lambda_1+\lambda_2<1$ ensuring that mean reverting. λ_1 capture the effects of previous shocks and

λ_2 previous dynamic conditional correlations on the current dynamic conditional correlation. For further details, and a critique of DCC, see Caporin and McAleer (2009, 2010). The expressions for $h_{ij\,t}$ are typically thought of as univariate GARCH models R_t is a matrix of conditional quasicorrelations, and $\widehat{\varepsilon_{t-1}}$ is a vector of standardized residuals, $D_t^{-1/2}$. R is a weighted average of the unconditional VCE of the standardized residuals and the unconditional mean of Q_t.

3.6.4 Parameter Estimation

A common issue using multivariate data for estimation is that the likelihood function becomes flat. Therefore, the choice of starting values is a crucial aspect of the estimation. Nevertheless, the remedy for the problem is simply to perform the estimation with different start values. The majority of empirical papers has concluded that financial data suffer from fat tailed distributions and this is often corrected by assuming the data follow Student-t distribution. However, the maximum likelihood (ML) method relies on the assumed distribution, then appointing an incorrect distribution to the maximum likelihood data then the ML is not consistent. But, by using the quasi maximum likelihood (QMLE) the estimation remains consistent even under misspecification. Furthermore, when dealing with models with conditional heteroskedasticity, the estimates are known to be asymptotically normal (Bollerslev&Wooldridge, 1992). Another thing that may be pointed out regarding the estimation procedure is that robust standard errors are used since they allow the sample to contain heteroskedasticity. In other words, the robust standard error better deals with non-constant variance. Let H_t (θ) be a positive definite $N\times N$ conditional covariance matrix of some $N\times 1$ residual vector ε_t, parameterized by the vector θ. Denoting the available information at time t_{-1} by Θ_{t-1} . We have:

E_{t-1} [ε_t| Θ_{t-1}] = 0…….. [3.42]

E_{t-1} [ε_t ε_t` | Θ_{t-1}] = H_t (θ)…….. [3.43]

Generally the conditional covariance matrix H_t (θ) is well specified based on a certain MGARCH model. Suppose there is an underlying parameter vector θ_0 which one wants to estimate using a given sample of T observations. The quasi maximum likelihood approach estimates θ_0 by maximizing the Gaussian log likelihood function.

Log $L_{T\,(\theta)}$= - $\frac{N\,T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(H\,t) - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t`\,H_t^{-1}\varepsilon_t$ ……....[3.44]

One need to notice its assumption that the time series treated should be stationary and the distribution of its residual is pre-defined as a conditional Gaussian distribution. When fitting a GARCH-model based on financial data, the conditional distribution of the returns has to be defined. Studies, for example Bollerslev (1987) and Hsieh (1989), illustrate that returns are not normally distributed. Instead, the Student-t distribution captures the observed kurtosis in empirical returns in a more sufficient way than the normal distribution. Returns have excess kurtosis and fatter tails than the normal distribution. Therefore, the Student-t distribution is more suitable (Reider, 2009) and should be checked.

3.6.5 Model Adequacy

The check of the adequacy of MGARCH models is essential in identifying whether a well specified MGARCH model can attain reliable estimates and inference. Graphical diagnostics for MGARCH models can be fulfilled by examining plots of the sample autocorrelation (ACF). To ensure the inference from the estimated parameters in the MGARCH model is enough valid, the residuals should be exhibited as a set of white noise with features like expected zero mean vector, no autocorrelations, constant variance, and normal distribution of the residuals.

4. RESULTS AND DISCUSSION

This study used stock market data obtained from Bloomberg and span the period 1999 week 1 to 2017 week 46. The data have information about the US dollar denominated weekly closing stock indices, developed weekly closing indices, African weekly closing indices and **weekly stock returns** are defined as 100 times the first differences of the log stock indices. The data in this study are analyzed using STATA 14.

4.1 Descriptive Statistics

Statistics	Stock market return						
	R USA	R Europe	R US dollar	R morocco	R Kenya	R Nigeria	R South Africa
Minimum	-14.90826	-18.50098	-3.921143	-15.34802	-11.95728	-27.14505	-17.79517
Maximum	12.95093	14.28442	5.284454	8.064941	13.66168	14.32889	22.42542
Mean	.0877869	.0247751	-.0006998	.0897807	.0236488	.0557682	.1618452
St.dev	2.443632	2.922972	1.123285	2.293871	2.426628	3.689811	3.741407
Skewness	-.3292136	-.7131125	.2097156	-.5515015	.1175214	-.7792211	-.4754097
Kurtosis	7.157415	7.079833	3.942519	8.073981	7.602631	8.451892	6.381254

Looking at Table 4.1, the average weekly returns for USA, Europe, Us dollar, morocco, Kenya, Nigeria and South Africa (per dollar)) were .0877869%, .0247751%, -.0006998% .0897807%, .0236488%, .0557682%, and .1618452% respectively, over the entire period. Except US dollar the average return were positive, which were an implication of the increasing trend in the developed stock market and selected African stock market .

The estimate of the standard deviation, which is the measure of volatility for USA, Europe, US dollar, morocco, Kenya, Nigeria and south Africa were 2.443632 2.922972 1.123285 2.293871 2.426628 3.689811 and 3.741407. Hence, we can say that they exhibit high variations in their returns.

If Skewness is greater than zero, the distribution is skewed to the right, having more observations on the left .From Table 4.1 except US dollar and Kenya stock market they have skewed to the

left (negatively skewed) which have more observation on the right. If Kurtosis is less than three (or if Kurtosis -3 is less than zero), the distribution has thicker tails and a lower peak compared to a normal distribution. Thus, from Table 4.1 above all stock market returns indices have higher peaks, as the kurtosis statistics are greater than 3, which were excess kurtosis. The Jarque-Bera statistics reject the null hypothesis that the returns are normally distributed for all stock markets at 5% level of significance.

Skewness and Kurtosis were deviate from normal distribution and it were an indication of asymmetric and leptokurtic distribution (Referring Table 4.11 on appendix A).

Time series plot of stock market price

As figure 4.7 up to figure 4.14 on Appendix A shows there is an increasing trend in the study period for all stock market except Nigeria.

Time series plot for returns of stock market

The weekly return series display volatility persistence properties, indicating that large return changes tend to be followed by large return changes of both sign and small return changes tend to be followed by small return changes, which were an indication of volatility in the developed and selected African stock market returns. Moreover, the plot shows that the volatilities of developed and selected African returns have a volatility clustering phenomenon during the study period indicates certain relation on their return volatility processes. That is, when there is a fluctuation of the developed stock market grew larger, the volatility of selected African stock markets also became larger for most of the times. This is the main motive for discussing the relationships of developed stock returns and selected African stock market returns in this study. (Referring figure 4.15 up to figure 22 on Appendix A)

4.2 Stationarity Test (unit root test)

Table4. 1 stationarity test

Stock market	ADF				PP			
	t-statistic			p-value	t-statistic			p- value
	1%	5%	10%		1%	5%	10%	
R US dollar	-3.430	-2.860	-2.570	0.0000	-3.430	-2.860	-2.570	0.0000
RUSA	-3.430	-2.860	-2.570	0.0000	3.430	-2.860	-2.570	0.0000
R Morocco	-2.330	-1.646	-1.282	0.0000	-3.960	-3.410	-3.120	0.0000
R Kenya	-2.330	-1.646	-1.282	0.0000	-3.960	-3.410	-3.120	0.0000
R Nigeria	-2.330	-1.646	-1.282	0.0000	-3.960	-3.410	-3.120	0.0000
R South Africa	-3.430	-2.860	-2.570	0.0000	3.430	-2.860	-2.570	0.0000
R European		29.500	21.800	0.0000	3.430	-2.860	-2.570	0.0000

Table 4.2 shows unit root test for developed and selected Africa stock market returns using Augmented Dickey-Fuller and Phillips-Perron in the return data. As we observed both tests conclude that there were no unit roots in the data series at 1%, 5% and 10% level of significance. And also time series plot of returns on Appendix A in figure 4.15 -4.22 shows that the returns were stationary. Thus ,the condition that a time series data should be stationarity were verified for each stock markets in this study and now the study could be proceed to the next step that is modelling volatility spill over from the developed to selected African stock markets. However, before modeling volatility it is necessary to model the mean equation.

Table 4.3 below represents the mean model.

4.3 Vector Autoregression Model

Table4.2 order of VAR model and adequacy checking

VAR	Developed Stock market	Selected African Stock market	US Dollar	AIC	BIC	χ^2 statistic	Test of Serial correlation	χ^2 statistic	ARCH Test
1	RUSA	Rmorocco		11.88776*	11.94776	8.0096	0.5318**	26.385	0.0000***
		R Kenya		12.22556*	12.28575	6.5272	0.68621**	87.476	0.0000***
		R Nigeria		13.10812	13.16856	28.722	0.00072		-
		R south Africa	R us dollar	12.41999*	12.48018	5.5529	0.78370**	30.162	0.0000***
	R European	Rmorocco		12.08455*	12.14454	10.274	0.32875**	25.316	0.0000***
		R Kenya		12.41768*	12.47797	10.231	0.33215**	87.067	0.0000***
		R Nigeria		13.29263	13.35307	33.319	0.00012		-
		R south Africa		12.38603*	12.44632	13.185	0.15440**	19.356	0.0000***
2	R USA	R morocco		11.90027	12.00536	7.0825	0.62814		-
		R Kenya		12.24001	12.3456	11.574	0.23840		-
		R Nigeria		13.09507	13.20128	22.217	0.00821		-
		R south africa	R us dollar	12.43303	12.53871	5.8605	0.73580		-
	R European	R morocco		12.09605	12.20121	7.0825	0.62853		-
		R Kenya		12.43141	12.53726	6.9173	0.64573		-
		R Nigeria		13.27728	13.38348	21.033	0.01250		-
		R south africa		12.39248	12.49833	6.3066	0.70888		-
3	R USA	R morocco		11.90437	12.0546	2.8525	0.96986		-
		R Kenya	R us dollar	12.22449	12.37583	7.0072	0.63636		-
		R Nigeria		13.10179*	13.25414	15.318	0.08256**	2.423	0.1196
		R south africa		12.44281	12.59427	13.828	0.12857		-
	R European	Rmorocco		12.10588	2.25636	1.6972	0.99540		-
		R Kenya		12.42647	12.57806	9.5293	0.38992		-
		R Nigeria		13.28508	13.43743	16.588	0.05556		-
		R south africa		12.40234	12.55406	11.203	0.26200		-

Key: * indicates that the selected mean model (VAR(p))based on small value of AIC and BIC.
**the selected mean model have no serial correlation.
*** The mean model have ARCH effect to be modeled by MGARCH family model.

4.3.1 Model Selection

The first stage in specifying the mean model is that selecting the appropriate order based on the information criteria. From Table 4.3 we observe that AIC and SBIC information criteria and this thesis is checked the vector autoregression model up to order 3, tri-variate VAR (p).

Based on AIC and SBIC statistics, the mean model for (RUSA, R morocco, R Us dollar),(RUSA, R Kenya, R Us dollar),(RUSA, R South Africa RUs dollar), (R Europe, R morocco, R Us dollar) (R Europe, R Kenya, R Us dollar) ,(R Europe, R South Africa, R Us dollar) were follow VAR (1) mean model. While (RUSA, R Nigeria, R us dollar) and (R Europe, R Nigeria, R us dollar) were followed VAR (3). In sum tri-variate VAR(1) for modelling the mean equation between developed stock market returns and selected African stock market returns(except for Nigeria) were appropriate. And also tri-variate VAR (3) is obtained for modeling the mean equation between developed stock market returns and selected African stock market return (Nigeria).

4.3.2 Model Adequacy Checking

Having selected the mean model it should be checked whether the fitted model fits the data well. For this purpose, this study conducted diagnostic tests for the presence of serial correlation and normality of the residuals. The presence of serial correlation in the residuals of the conditional mean equation is tested using the Lagrange Multiplier (LM) test. The null hypothesis asserts that there is no serial correlation in the residual series up to lag 2. The Breusch–Godfrey serial correlation LM test results in Table 4.3 above provided that there is no serial correlation in the residuals of the mean equation. Hence, there were no serial correlations in the residuals for selected mean model.

The Jarque-Bera statistic Table 4.5(on Appendix) is significant, and hence, rejecting the null hypothesis of normality. This indicates that the residuals of the fitted model are not normally distributed at 5 %level of significance. The plots reported in Figures 4.23 to figure 4.29 (on Appendix A) shows that fat tails, which is excess kurtosis and having leptokurtic distribution for all stock market. The reason is that most financial time series have the properties of fat tails and positive correlation in squared residual results leptokurtic distribution and deviation from normality. And these properties of financial multivariate time series are not captured by VAR (p) model rather it will be captured by MGARCH family model in this study.

4.3.3 Vector Autoregression Model Stability

Table 4.10 (on appendix A) shows that all the Eigen values lie inside the unit circle that is modulus greater than one. Thus, the selected mean model for developed stock market returns and selected African stock market returns (tri-variate VAR) satisfies stability condition and it ensures the stationarity of the returns.

4.3.4 Granger Causality Test

Establishing causality is important because it provides us with an understanding of which stock market affects in the system. Table 4.4 below shows the result from running a Granger Causality test based on Wald test on the returns. There is a unidirectional causality obtained from USA to Kenya, Nigeria and Europe to Kenya at 5%level of significance. This shows that there is a unidirectional causality from developed stock market returns to selected African stock market returns. But there is a bidirectional causality running from Europe to Nigeria in the short run. The main issue in this thesis is the time varying correlation from developed stock market to selected stock African markets and this could be captured by multivariate GARCH family model.

Table4.3 Granger causality test

Null hypothesis	F statistic	p- value
R USA does not have granger cause R morocco	.41226	0.814
R morocco does not have granger cause R USA	2.0478	0.359
R Kenya does not have granger cause R USA	.05177	0.820
R USA does not have granger cause R Kenya	14.203	0.000
R Nigeria does not have granger cause R USA	4.5079	0.212
R USA does not have granger cause R Nigeria	11.823	0.008
R USA does not have granger cause R South Africa	.34002	0.560
R south Africa does not have granger cause R USA	.4119	0.521
R European does not have granger cause R morocco	.00017	0.990
R morocco does not have granger cause R European	.30053	0.584
R Kenya does not have granger cause R European	.33983	0.560
R European does not have granger cause R Kenya	20.815	0.000
R European does not have granger cause R Nigeria	12.614	0.006
R Nigeria does not have granger cause R European	24.213	0.000
R European does not have granger cause R south Africa	.18855	0.664
R south Africa does not have granger cause R European	.40942	0.522

4.4 Test for ARCH effects

Based on the residuals from the mean equation it is possible to test for the existence of ARCH effects which will allow analysis using GARCH family models. The ARCH LM test helps to test the hypothesis that there is no ARCH effect up to lag p. If the test provides significant results,

then it is possible to conclude that there is an ARCH effect up to lag p. The results of ARCH LM test for the residuals of our tri-variate VAR (1) model are displayed in Table 4.3 with mean model to conserve space. The results indicate that the null hypothesis of no ARCH effect in the first three lags of residuals from the mean equation for the return series are rejected at 5%level of significance. This implies that the conditional covariance of the weekly return series of the developed stock market and selected African stock market (except Nigeria) is not time invariant that is time variant and should be modeled by MGARCH family model. While tri-variate VAR(3) selected mean model for developed stock markets(USA, Europe) and African (Nigeria) stock market have no ARCH effect as we observed from Table 4.3at 5% level of significance. Therefore, there was no volatility from developed stock market to Nigeria and no need of MGARCH family model, rather the study finished the task for developed stock markets against Nigeria on tri-variate VAR (3) mean model (refer on Table 4.12 and 4.13 on Appendix A).

Now this thesis is in the position of modelling volatility spillover from developed stock markets to selected African stock markets (except Nigeria) using multivariate GARCH family model like CCC and DCC model.

Table4.4 Tri-variate-GARCH (1,1) CCC and DCC under normal distribution

CCC									DCC					
Stock market	Selected Africa	Us		Coefficient		Z-statistic		p-value	Coefficient		Z-value		p-value	
				RUSA /Europe	s.Africa	RUSA/ Europe	s.Africa	RUSA/ Europe	s.Africa	Rusa / Europe	s.Africa	RUSA /Europe	S.Africa	RUSA /Europe	S.Afirca
R USA	R morocco		C	.1475173	.3391649	2.54	3.55	0.011	0.000	.1860809	.3122128	2.81	3.53	0.005	0.000
			arch1	.1263274	.124143	5.14	5.00	0.000	0.000	.135277	.1257505	5.26	5.07	0.000	0.000
			garch 1	.8489799	.8088115	28.76	23.28	0.000	0.000	.8318357	.8148897	26.19	24.47	0.000	0.000
			Corr	-	.080508	-	2.53	-	0.011	-	.0898873	-	1.29	-	0.198
			λ_1	-						.0267971		4.79		0.000	
			λ_2	-						.9490271		91.73		0.000	
	R Kenya		C	.1892413	.6541897	3.27	3.42	0.001	0.001	.2095022	.6468493	2.98	3.40	0.003	0.001
			Arch1	.1327797	.2151363	5.31	4.78	0.000	0.000	.13774	.2160493	5.40	4.80	0.000	0.000
			Garch 1	.8407294	.6762457	28.12	10.34	0.000	0.000	.823946	.6826921	25.79	10.64	0.000	0.000
			Corr	-	.012761	-	0.40	-	0.691	-	.0258394	-	0.42	-	0.676
			λ_1	-						.0257306		4.47		0.000	
			λ_2	-						.9455671		73.32		0.000	
	R south Africa		C	.1247498	.6800911	2.55	2.59	0.011	0.010	.120782	.3972136	2.60	2.63	0.009	0.008
			Arch1	.0961767	.0505806	5.20	3.98	0.000	0.000	.1048012	.06272	5.76	5.21	0.000	0.000
			Garch 1	.8797813	.8921724	36.33	29.14	0.000	0.000	.8743371	.9071614	38.40	46.04	0.000	0.000
			Corr	-	.598381	-	29.16	-	0.000	-	.6233915	-	12.40	-	0.000
			λ_1	-						.0357824		5.98		0.000	
			λ_2	-						.9418485		96.23		0.000	
R European	R morocco		C	.5724796	.351832	3.67	3.49	0.000	0.000	.6282717	.3201813	3.91	3.43	0.000	0.001
			Arch1	.178403	.125306	5.81	4.99	0.000	0.000	.1897107	.1328574	6.00	5.19	0.000	0.000
			Garch 1	.7562164	.8052912	19.65	22.51	0.000	0.000	.7404959	.8096169	18.96	23.76	0.000	0.000
			Corr	-	.237577	-	7.85	-	0.000	-	.279661	-	3.68	-	0.000
			λ_1	-						.0347548		5.81		0.000	
			λ_2	-						.9436163		90.21		0.000	
	R Kenya		C	70576	.643343	4.01	3.43	0.000	0.001	.7073127	.6293009	4.28	3.46	0.000	0.001
			Arch1	.180878	.213987	5.80	4.83	0.000	0.000	.1897217	.2242137	6.03	4.96	0.000	0.000
			Garch 1	.7349166	.6801132	18.22	10.56	0.000	0.000	.7289026	.6848264	18.83	11.09	0.000	0.000
			Corr	-	.039743	-	1.24	-	0.217	-	.027402	-	0.38	-	0.704
			λ_1	-						.0341493		5.53		0.000	
			λ_2	-						.9394861		76.33		0.000	
	R south Africa		C	.6439853	-.038201	3.64	-1.08	0.000	0.281	.559851	1.014947	3.83	3.18	0.000	0.001
			Arch1	.1281915	.084209	5.50	4.30	0.000	0.000	.147403	.1012364	6.42	5.25	0.000	0.000
			Garch 1	.7831716	.804600	19.9	16.70	0.000	0.000	.7847694	.8287273	23.29	23.54	0.000	0.000
			Corr	-	.751083	-	53.76	-	0.000	-	.7854244	-	24.70	-	0.000
			λ_1	-						.0469698		6.48		0.000	
			λ_2	-						.926445		75.42		0.000	

Table4.5 Tri-variate-GARCH CCC and DCC under student t-distribution (v=6 df)

Stock market	Selected Africa	Us	CCC							DCC					
				Coefficient		Z-statistic		p-value		Coefficient		Z-value		p-value	
				RUSA /Europe	s.Africa	RUSA/ Europe	s.Africa	RUSA /Europe	s. Africa	R usa /Europe	s.Africa	RUSA /Europe	S.Africa	RUSA /Europe	S.Africa
R USA	R morocco		C	.113573	.2347747	1.95	2.73	0.051	0.006	.1378132	.2268012	2.06	2.70	0.039	0.007
			arch1	.1237299	.0986925	4.19	4.08	0.000	0.000	.1277768	.100135	4.09	4.16	0.000	0.000
			garch 1	.8656408	8546104	27.59	25.64	0.000	0.000	.8569313	. 8560157	24.85	26.24	0.000	0.000
			Corr	-	0546138	-	1.57	-	0.117	-	.0332533	-	0.52	-	0.603
			λ_1	-						.0238763		3.39		0.001	
			λ_2	-						.9453617		54.81		0.000	
	R Kenya		C	.1102902	.5938197	1.82	2.71	0.069	0.007	.1412795	.0256502	2.01	1.81	0.044	0.070
			Arch1	.1313678	.1983492	4.30	3.77	0.000	0.000	.8495422	.0489152	24.06	3.30	0.000	0.001
			Garch 1	.8588647	.6952376	26.57	8.93	0.000	0.000	.823946	.9381586	25.79	53.36	0.000	0.000
			Corr	-	-.017794	-	-0.51	-	0.612	-	-.0461037	-	-0.64	-	0.523
			λ_1	-						.0299292		4.00		0.000	
			λ_2	-						.9408992		53.85		0.000	
	R south Africa		C	.1019587	.5345688	2.26	2.44	0.024	0.015	.0909622	.3719525	2.16	2.50	0.031	0.013
			Arch1	.0852811	.0488035	4.36	3.37	0.000	0.001	.096943	.0580214	4.90	4.18	0.000	0.000
			Garch 1	.8973515	.9109383	39.28	33.80	0.000	0.000	.8743371	.9182128	41.89	46.50	0.000	0.000
			Corr	-	.575719	-	24.42	-	0.000	-	.5460373	-	8.21	-	0.000
			λ_1	-						.0357824		5.98		0.000	
			λ_2	-						.9418485		96.23		0.000	
R European	R morocco		C	.4997304	.278356	2.71	2.66	0.007	0.008	.5890797	.2711349	2.81	2.64	0.005	0.008
			Arch1	.1564577	.105745	4.25	3.95	0.000	0.000	.177189	.1106665	4.36	4.11	0.000	0.000
			Garch 1	.7903193	.8389183	16.59	21.40	0.000	0.000	.7658944	8393337	14.71	22.06	0.000	0.000
			Corr	-	.227167	-	6.84	-	0.000	-	.2284886	-	3.00	-	0.003
			λ_1	-						.0310303		4.34		0.000	
			λ_2	-						.9456039		70.15		0.000	
	R Kenya		C	.5107748	.689332	2.70	2.93	0.007	0.003	.566084	.6937909	2.89	2.99	0.004	0.003
			Arch1	1608885	.218696	4.30	4.05	0.000	0.000	.1712638	.2286294	4.42	4.96	0.000	0.000
			Garch 1	.7850362	.6622239	16.32	8.32	0.000	0.000	.77350	.6591017	15.95	8.43	0.000	0.000
			Corr	-	.025924	-	0.74	-	0.459	-	-.0038564	-	-0.04	-	0.965
			λ_1	-						.0335556		5.49		0.000	
			λ_2	-						.9449254		94.05		0.000	
	R south Africa		C	.3138351	.779779	2.13	2.11	0.033	0.035	.3403671	.6625677	2.47	2.40	0.014	0.016
			Arch1	.0876786	.060903	3.56	2.85	0.000	0.003	.1196651	.0803448	4.24	3.75	0.000	0.000
			Garch 1	.8675919	.8791412	21.89	19.65	0.000	0.000	.8440062	.8779641	22.27	25.71	0.000	0.000
			Corr	-	.739356	-	46.35	-	0.000	-	.7413058	-	17.67	-	0.000
			λ_1	-						.0440441		5.77		0.000	
			λ_2	-						.933892		76.91		0.000	

4.5 Model Comparison

The choice of the conditional correlation model in this study was based on adjustment parameters (λ_1 ,λ_2,). As Table 4.5 and 4.6 provides λ_1 and λ_2 were significant for all stock markets. Thus, the null hypothesis that the adjustment parameter equal to zero, that is $\lambda_1 = \lambda_2 = 0$ is rejected at 5%level of significance for developed stock markets and selected African stock markets. This implies that there is a time varying conditional correlation between developed stock markets and selected African (except Nigeria) stock markets. Hence, the assumption of DCC model reduced to CCC model is not supported by the data. Thus, volatility spillover from developed stock markets to selected African stock markets could be captured by DCC model in this thesis.

The choice of error distribution that the DCC model follows to capture conditional volatility spillover in the stock markets is compared based on log-likelihood statistic in this study.

Table4. 6 log-likelihood statistic

Log-likelihood				
Developed stock market	Selected Africa stock market		DCC t -dist ,v=6	DCC normal distribution
USA	Morocco	Us dollar	-5512.425	-5571.155
	Kenya		-5640.526	-5710.858
	South Africa		-5795.788	-5829.871
Europe	Morocco		-5614.601	-5669.039
	Kenya		-5741.65	-5807.344
	South Africa		-5789.077	-5825.141

The Log-likelihood on Table 4.7 shows that tri-variate DCC (1,1) model with student distribution having 6 degree of freedom is preferred model. This is also supported by the descriptive statistics in which the returns were leptokurtic distribution and negatively skewed that is deviation from normal distribution,. Moreover, the return data is non-normal, rejecting the Jarque-Bera test at 5% level. Therefore, tri-variate DCC model applied to the stock market returns are fitted with a Student-t distribution.

Table 4.7 Estimated Tri-variate-GARCH DCC (1, 1) model under student t-distribution (v=6df)

DCC									
Stock market	Selected Africa	Us dollar		Coefficient		Z-value		p-value	
				R USA /Europe	Selected Africa	RUSA /Europe	Selected Africa	RUSA/Europe	Selected Africa
RUSA	R morocco		C	.1378132	.2268012	2.06	2.70	0.039	0.007
			arch1	.1277768	.100135	4.09	4.16	0.000	0.000
			garch1	.8569313	. 8560157	24.85	26.24	0.000	0.000
			Corr	-	.0332533	-	0.52	-	0.603
			λ_1	.0238763		3.39		0.001	
			λ_2	.9453617		54.81		0.000	
	R Kenya		C	.1412795	.0256502	2.01	1.81	0.044	0.070
			Arch1	.8495422	.0489152	24.06	3.30	0.000	0.001
			Garch1	.823946	.9381586	25.79	53.36	0.000	0.000
			Corr	-	-.0461037	-	-0.64	-	0.523
			λ_1	.0299292		4.00		0.000	
			λ_2	.9408992		53.85		0.000	
	R south Africa		C	.0909622	.3719525	2.16	2.50	0.031	0.013
			Arch1	.096943	.0580214	4.90	4.18	0.000	0.000
			Garch1	.8743371	.9182128	41.89	46.50	0.000	0.000
			Corr	-	.5460373	-	8.21	-	0.000
			λ_1	.0357824		5.98		0.000	
			λ_2	.9418485		96.23		0.000	
R European	R morocco		C	.5890797	.2711349	2.81	2.64	0.005	0.008
			Arch1	.177189	.1106665	4.36	4.11	0.000	0.000
			Garch1	.7658944	.8393337	14.71	22.06	0.000	0.000
			Corr	-	.2284886	-	3.00	-	0.003
			λ_1	.0310303		4.34		0.000	
			λ_2	.9456039		70.15		0.000	
	R Kenya		C	.566084	.6937909	2.89	2.99	0.004	0.003
			Arch1	.1712638	.2286294	4.42	4.96	0.000	0.000
			Garch1	.77350	.6591017	15.95	8.43	0.000	0.000
			Corr	-	-.0038564	-	-0.04	-	0.965
			λ_1	.0335556		5.49		0.000	
			λ_2	.9449254		94.05		0.000	
	R south Africa		C	.3403671	.6625677	2.47	2.40	0.014	0.016
			Arch1	.1196651	.0803448	4.24	3.75	0.000	0.000
			Garch1	.8440062	.8779641	22.27	25.71	0.000	0.000
			Corr	-	.7413058	-	17.67	-	0.000
			λ_1	.0440441		5.77		0.000	
			λ_2	.933892		76.91		0.000	

4.5 Model Adequacy Checking

Checking the adequacy of MGARCH models is essential in identifying whether a well specified MGARCH model can obtain reliable estimates and inference. Graphical diagnostics for MGARCH models can be done by examining plots of the sample autocorrelation (ACF).To ensure the inference from the estimated parameters in the MGARCH model is enough valid, the residuals should exhibit a set of white noise features like expected zero vector, no autocorrelations, constant variance, and normal distribution of the residuals. The autocorrelation functions for the squared process are shown to be useful in identifying and checking time series behavior in the conditional variance equation of the GARCH form.

4.5.1 Residual Analysis

Table4.8 Portmanteau test of white noise residuals from DCC model

Returns	Residuals	Q statistic	p-value
Morocco	Standardized residuals	48.1414	0.1766
	Squared standardized residuals	28.4238	0.9145
Kenya	Standardized residuals	75.4689	0.0006
	Squared standardized residuals	63.3018	0.0109
South Africa	Standardized residuals	25.9220	0.9584
	Squared standardized residuals	42.4749	0.3649
USA	Standardized residuals	40.9799	0.4273
	Squared standardized residuals	26.8491	0.9446
USD	Standardized residuals	52.5069	0.0889
	Squared standardized residuals	40.8857	0.4314
Europe	Standardized residuals	31.7814	0.8198
	Squared standardized residuals	41.9207	0.3875

Table 4.9 shows that the portmanteau test of white noise to tests the null hypothesis that there is no autocorrelation in the residuals and squared residuals. Since the p-value are larger than 5% level of significance there were no serial correlation in the residuals and squared residuals after fitting the tri-variate DCC with t-distribution model except Kenya in this study. The DCC model is not well fitted the conditional return correlation from developed stock markets to Kenya. The estimated conditional return correlation between developed stock market and Kenya were insignificant. The correlogram for the standardized and squared standardized residuals are given in Figure 4.34 and 35(Appendix B). It shows that the residuals are not auto correlated for stock

market returns except Kenya. By looking at the ACF graphs, it can be determined whether the processed data has any trace of correlation in the residuals. If more than 5 % of the lags in the autocorrelation plot fall outside the confidence interval, the residuals cannot be treated as white noise. However, less than five out of 100 lags fall outside the confidence level.

4.5.2Normality of Standardized Residuals

GARCH estimates could be sensitive to the assumption of normally distributed errors. So it is important to check the extent to which this assumption is correct. Since the standardized errors are not directly observable and they have to be estimated, chi-squared based tests such as the skewness and kurtosis tests for normality are not strictly speaking applicable. Instead it is advisable to plot the quantiles of the standardized residuals against the quantiles of the standardized normal distribution (Q-Q plot) and check if they are similar (Sourafel, 2016). Figure 4.30-4.33 is the q-q plots of the standardized residuals from the selected DCC model, Appendix B. In all of the plots it appears that we have approximately normally distributed standardized errors, except for deviations at the start and end tails.

Predicted DCC plot

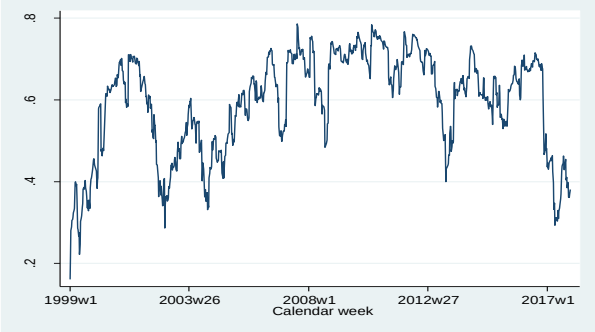

Figure 4.1correlation plot between USA and South Africa

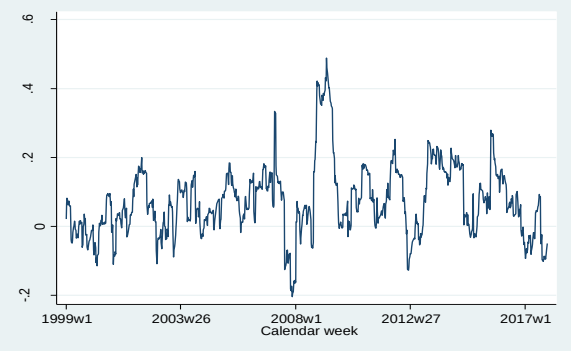

Figure 4.2 correlation plot between USA and Kenya

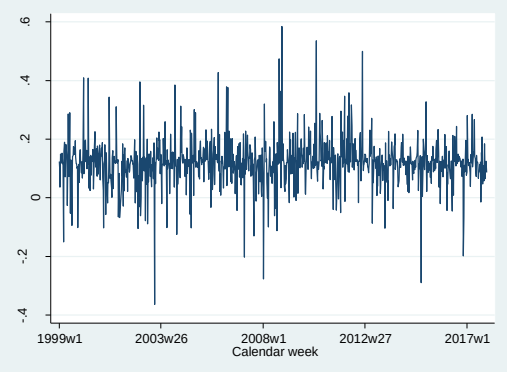

Figure 4.3 correlation plot between USA and morocco

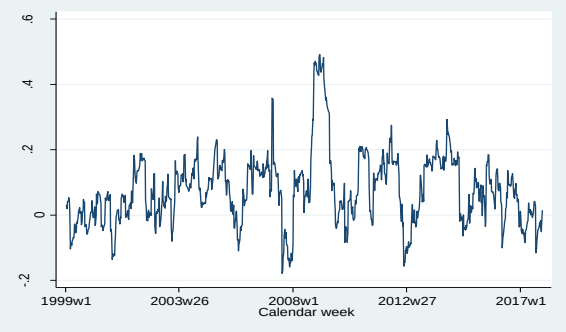

Figure 4.5 correlation plot between Europe and Kenya

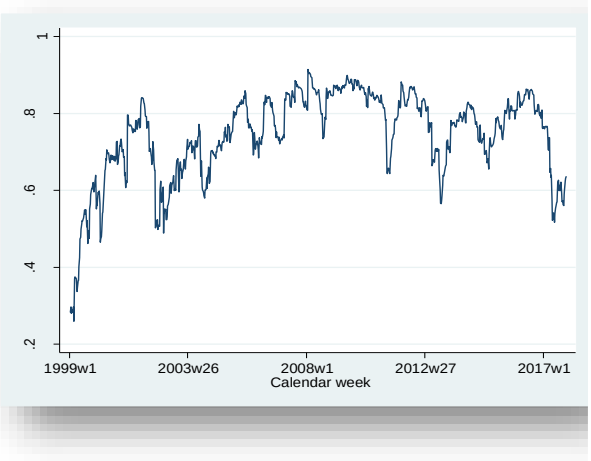

Figure 4.4 correlation plot between Europe and south africa

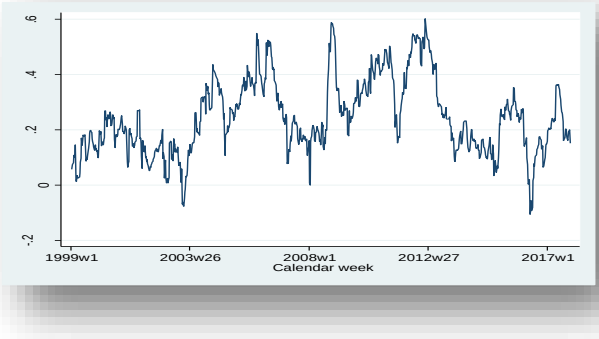

Figure 4.6 DCC correlation plot between Europe and morocco

4.6 DISCUSSION

Table 4.8 reports the result of estimated tri-variate DCC (1, 1) model for developed stock, selected Africa stock and us dollar markets. The tri-variate DCC model applied in the analysis allows for a time varying correlation structure. The coefficient *c* corresponds to the mean equation parameter, while *arch* and *garch* represents the conditional covariance of developed stock markets and selected Africa (except for Nigeria) stock markets using US dollar as market common currency. As reflected in the Table 4.8, all parameters are positive and significant at 5% levels of significance. There are very significant GARCH effects in all equations based on p-value at 5% level of significance. The volatility persistence in these markets is measured by the sum of arch and garch, and looking at Table 4.8 the sums of the variance equation parameters *arch* and *garch* are close to one, indicating that high persistence in conditional

covariance. Volatility persistence deals with the nature of volatility and whether the current period's volatility is affected by past periods' volatility or not.

The magnitudes of the lambda parameters indicate that the evolution of the conditional covariance depends more on their past values than on lagged residuals' innovations the parameter λ_2 , is highly significant for all stock markets, with a value varying from 0.9408992 to 0.9453617. Similarly, the recent co-movements in correlation (captured by the parameter, λ_1) are highly significant for all markets. The sum $\lambda_1 + \lambda_2 < 1$ provided the process described by the model is said to be mean reverting for all combination of developed stock market with selected African (except Nigeria) stock markets. The implication of this is that after a shock occurs, the correlations will in time return to the long-run unconditional level. And also the sum of lambda less than one ensures the tri-variate DCC model is positive definite in this thesis.

The sizable conditional returns correlation at Table 4.8 and figure 4.1 up to figure 4.6 shows the interaction between the developed stock markets and selected African stock markets returns. The estimated conditional returns correlation between the volatilities of USA vs South Africa, Europe vs morocco and Europe vs South Africa (.5460373), (.2284886) and (.7413058) respectively are positive and significant at 5% level of significance. This means that high volatility in the Europe and USA stock market are associated with high volatility in the South Africa and morocco stock markets and vice versa and there are strong correlation .

Figure 4.1-4.6 shows that the plot of predicted conditional returns correlation between the developed stock markets and selected African stock markets volatilities varies over time. For instance USA with South Africa, Europe with morocco and Europe with South Africa stock market returns volatility varies over time. This behavior is a property of the dynamic and time-varying conditional correlation MGARCH models. In a constant conditional correlation MGARCH model, correlations do not vary over time and the line would be flat.

This suggests that the return of USA vs return of South Africa, Europe vs morocco and Europe vs South Africa volatility tend to move in the same directions. That is there are volatility spillovers from USA to South Africa, Europe to morocco and Europe to South Africa. Which means the lagged volatility of USA stock market return affects the current volatility of South

Africa stock market. That is if there is a market disturbance let say price change in USA stock market it have significant effect on current stock market of South Africa.

Likewise, lagged volatility of Europe stock market return has significant effect on current volatility of morocco and South Africa stock market return and if there is a market disturbance let say price change in Europe stock market it have significant effect on south Africa and morocco stock market return.

It seems that this result supports the conventional expectation that the volatility spillover is usually rises from developed stock market to selected African stock markets. However, there are insignificant correlation between return of USA vs morocco, USA vs Kenya and Europe vs Kenya returns stock market. There are negative insignificant correlations from USA to Kenya and from Europe to Kenya stock market.

5. CONCLUSION AND RECOMMENDATION

The main purpose of this thesis is modelling volatility spillovers from developed stock markets to selected African stock markets. In this case first the mean equations are fitted and the adequacy of the model is checked. Tri-variate VAR (1) and VAR (3) model are fitted. However the Tri-variate VAR (3) model have no arch effect (no volatility). Volatility spillover from developed stock markets to selected African stock markets is captured by conditional correlation models. From the candidate conditional correlation models the Tri-variate DCC (1, 1) model with t-error distribution having 6 degree of freedom is appropriate to capture volatility spillover in this thesis. Based on the result the analysis points to the following conclusions:

From Wald test of granger causality test of return there is a unidirectional causality rising from USA to Kenya, USA to Nigeria and Europe to Kenya at 5%level of significance. And there is bidirectional causality between Europe and Nigeria in the short run.

This thesis concludes that there are increasing trends in the study period between developed stock market and selected African stock market and volatility spillovers are increasing over time except Nigeria and Kenya. Additionally, there are strong positive conditional return correlations which rising from USA to South Africa, Europe to South Africa and Europe to morocco stock market return. Moreover, this thesis concludes that there is a volatility spillover from developed stock to selected African stock markets to morocco and South Africa.

This thesis attempts to recommend that further researcher can investigate the volatility spillover from developed stock market to African stock market using conditional covariance model like BEKK and diagonal VEC and (s)he may choose among the candidate model.

Additionally, further researcher may investigate the volatility spillover from developed stock market to African stock markets by considering world financial crisis like 2008, to investigate volatility spillover effect before and after crisis.

Last but not least, the researcher can investigate by dividing the study period in to two subsamples and forecasting the volatility spillover effect which will arise from developed stock markets to African stock markets.

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Appendix A

Table4. 9 vector autoregression model stability condition

Var(1) Rusa, Rmorocco, Rus dollar

Eigenvalue	Modulus
.1320867	.132087
.08949659	.089497
.02888148	.028881

Var(1) Rusa ,R Kenya R us dollar

Eigenvalue	Modulus
.1494608	.149461
.1291224	.129122
.01134854	.011349

Var(3) Rusa ,R nigeria R us dollar

Eigenvalue	Modulus
.2608869 + .3654354i	.449004
.2608869 - .3654354i	.449004
.3944971 + .1006309i	.40713
.3944971 - .1006309i	.40713
.3075887 + .01846631i	.308143
.3075887 - .01846631i	.308143
.147102 + .2603488i	.299033
.147102 - .2603488i	.299033
.07690335	.076903

Var(1) Rusa ,Rsouth africa ,R us dollar

Eigenvalue	Modulus
.150312	.150312
.07048167	.070482
.02731405	.027314

Var(1) R Europe R morocco R us dollar

Eigenvalue	Modulus
.1094527	.109453
.08890804	.088908
.02980738	.029807

Var(1) R europe,R Kenya R us dollar

Eigenvalue	Modulus
.1542747	.154275
.1146098	.11461
.01482206	.014822

var(3) Reurope, Rnigeria ,Rusdollar

Eigenvalue	Modulus
.2562505 + .3862304i	.463506
.2562505 - .3862304i	.463506
.4106812 + .1777425i	.447495
.4106812 - .1777425i	.447495
.1667574 + .3219051i	.362534
.1667574 - .3219051i	.362534
.341494 + .04188715i	.344053
.341494 - .04188715i	.344053
.0668623	.066862

Var (1) Reuropea,Rsouth_africa Rusdollar

Eigenvalue	Modulus
.117116	.117116
.04148468	.041485
.02345742	.023457

All the eigenvalues lie inside the unit circle.

VAR satisfies stability condition.

Table4.10 normality test Jarque-Bera test

Normality RUSA, R MOR, Rus dollar

Equation	chi2	df	Prob > chi2
Rusa	709.131	2	0.00000
Rmorocco	816.141	2	0.00000
Rusdollar	2.316	2	0.31410
ALL	1527.589	6	0.00000

Normality RUSA,Rkenya,R us dollar

Equation	chi2	df	Prob > chi2
Rusa	695.451	2	0.00000
Rkenya	721.186	2	0.00000
Rusdollar	14.100	2	0.00087
ALL	1430.737	6	0.00000

normality RUSA,RSA,Rus dollar

Equation	chi2	df	Prob > chi2
Rusa	680.191	2	0.00000
Rsouth_africa	102.502	2	0.00000
Rusdollar	9.731	2	0.00771
ALL	792.424	6	0.00000

Normality R EU, RMOR, Rus dollar

Equation	chi2	df	Prob > chi2
Reurope	776.020	2	0.00000
Rmorocco	826.940	2	0.00000
Rusdollar	3.758	2	0.15277
ALL	1606.718	6	0.00000

Normality REU, Rkenya , RUsdollar

Equation	chi2	Df	Prob > chi2
Reurope	762.667	2	0.00000
Rkenya	789.065	2	0.00000
Rusdollar	10.060	2	0.00654
ALL	1561.791	6	0.00000

Normality REU,Rnigeria,Rus dollar

Equation	chi2	df	Prob > chi2
Reurope	698.375	2	0.00000
Rnigeria	1369.498	2	0.00000
Rusdollar	13.146	2	0.00140
ALL	2081.019	6	0.00000

normality REU, RSA, Rus dollar

Equation	chi2	df	Prob > chi2
Reurope	739.526	2	0.00000
Rsouth_africa	71.296	2	0.00000
Rusdollar	9.249	2	0.00981
ALL	820.072	6	0.00000

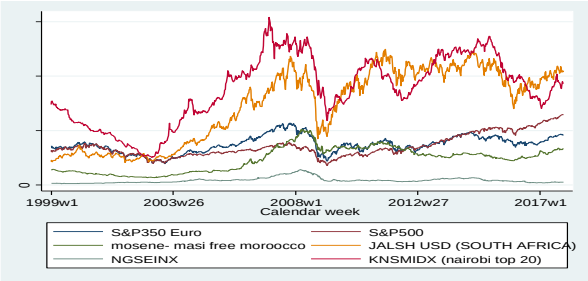

Figure 4.7 Time series of all stock market price

Figure4. 8 .Time series plot of Europe

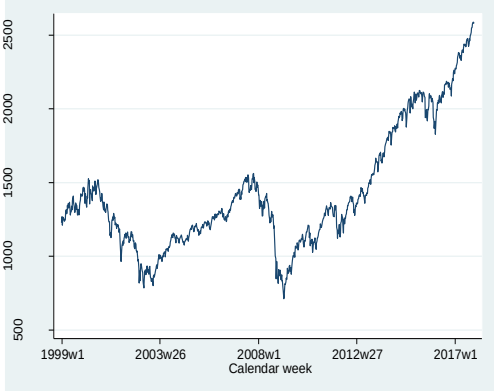

Figure 4.9 Time series plot of USA

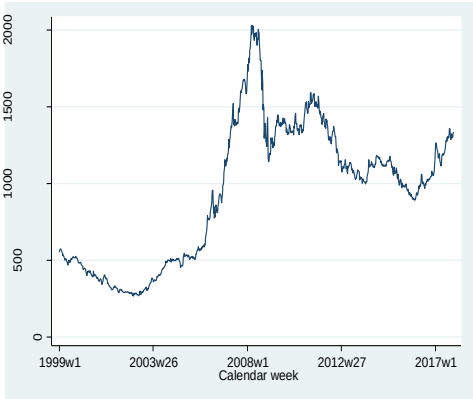

Figure 4.10 Time series plot of morocco

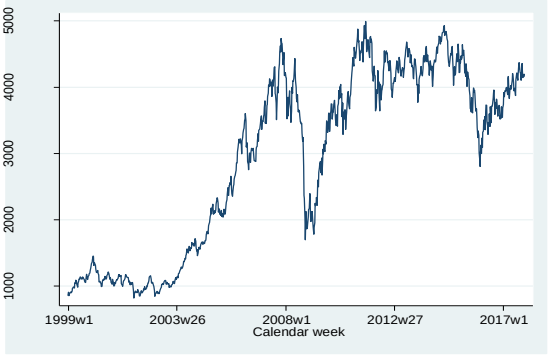

Figure 4.11 time series plot of south Africa

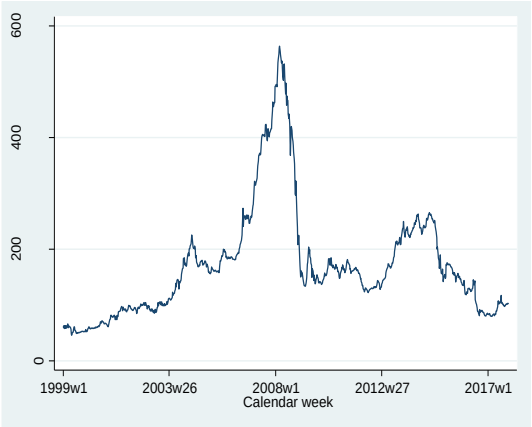

Figure4. 12 time series plot of Nigeria

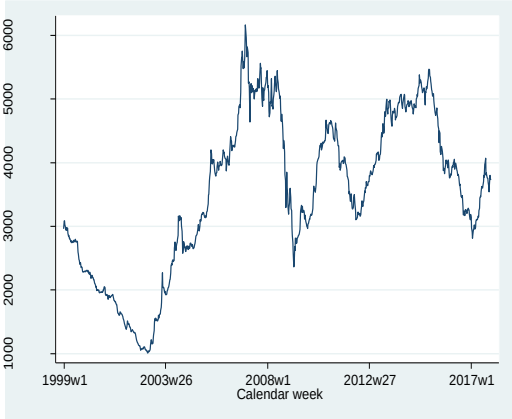

Figure 4.13 time series plot of Kenya

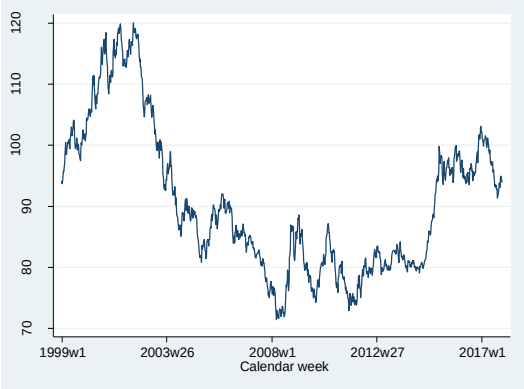

Figure 4.14 time series plot of Us dollar

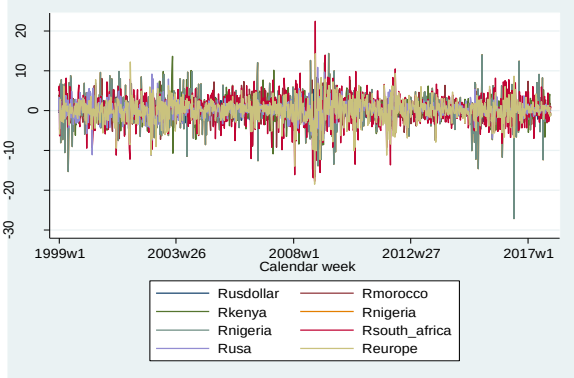

Figure 4.15 time series of stock market returns

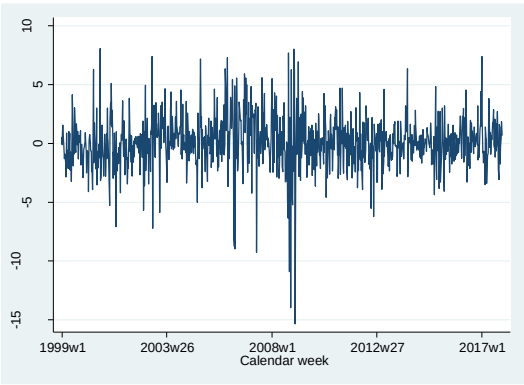

Figure 4.17 time series plot of morocco return

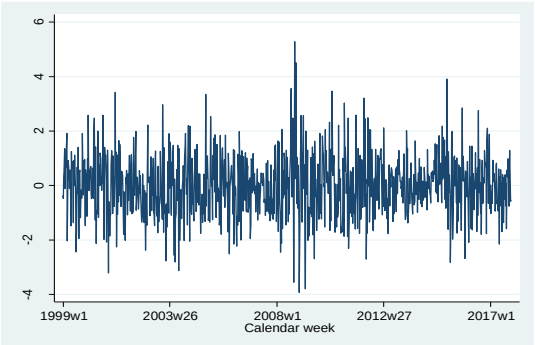

Figure 4.16 time series plot of us dollar return

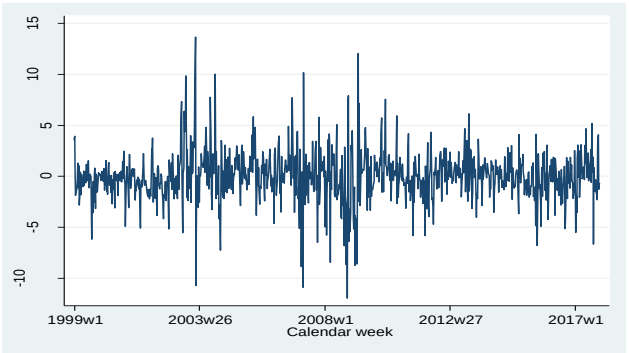

Figure 4.18 time series plot of Kenya return

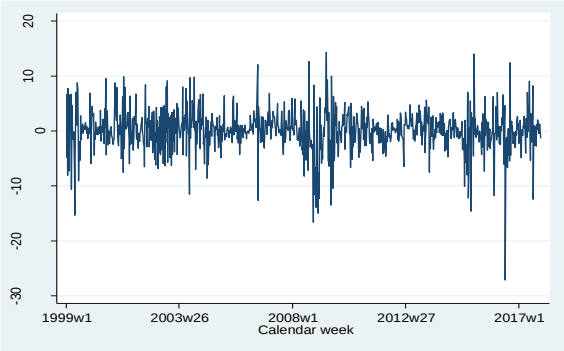

Figure4. 19 time series plot of Nigeria return

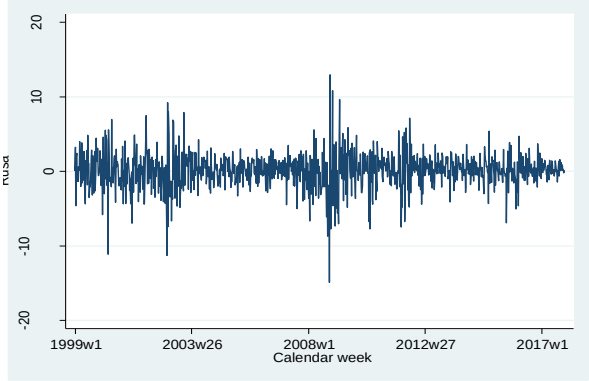

Figure 4.21 time series plot of USA return

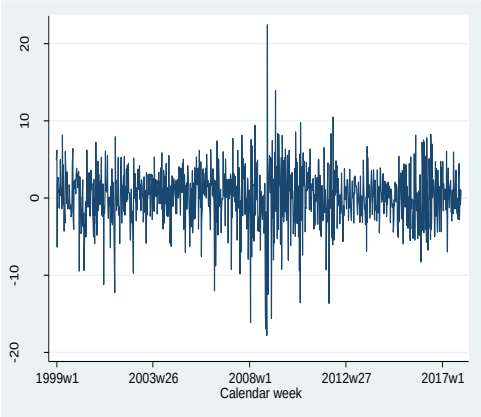

Figure4.20 time series plot of South Africa return

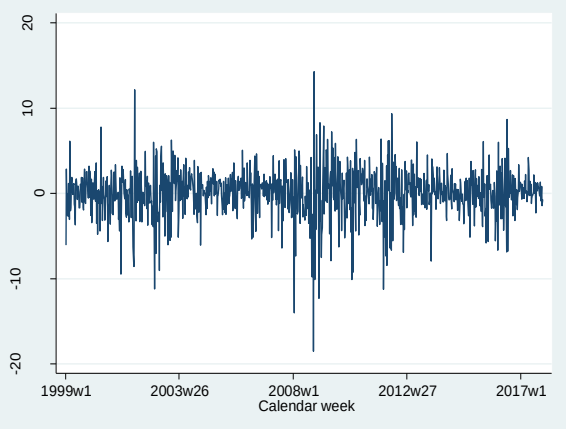

Figure4. 22time series plot of Europe

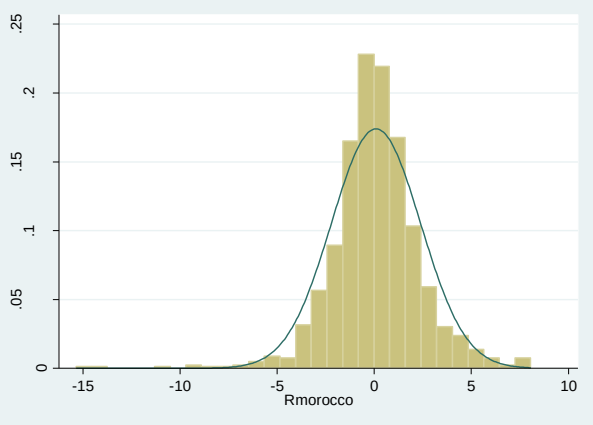

Figure4. 23normal probability plots of morocco

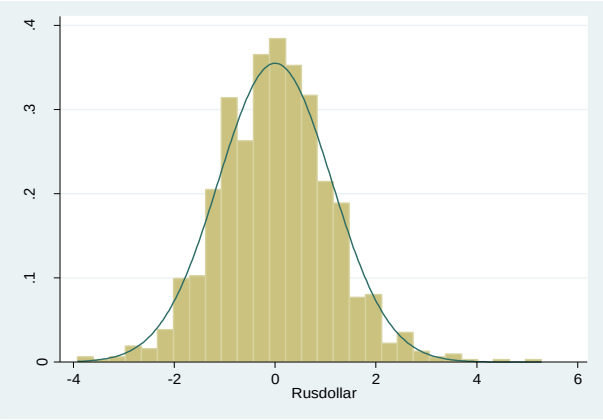

Figure4. 24 normal probability plot of us dollar

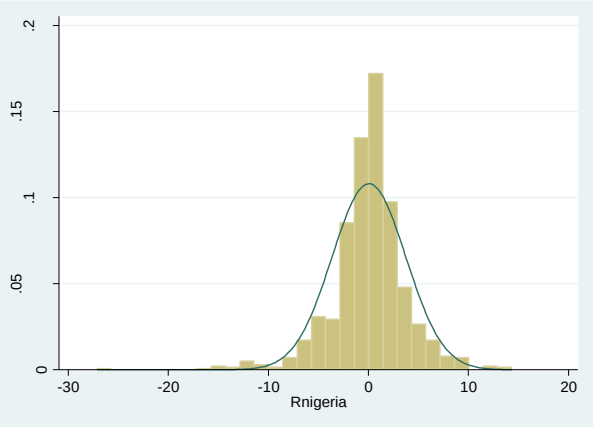

Figure 4.25 normal probability of Nigeria

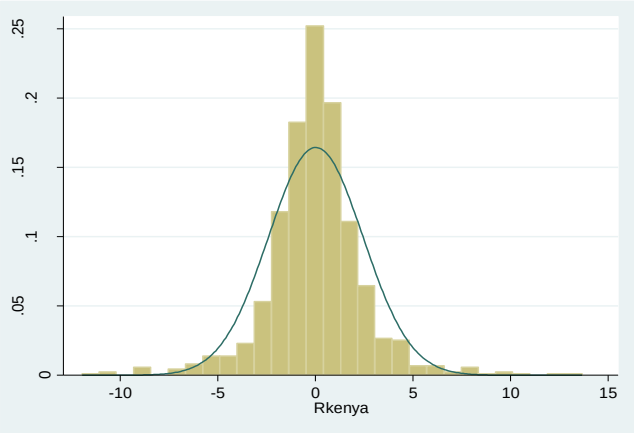

Figure 4.27 normal probability plot of Kenya

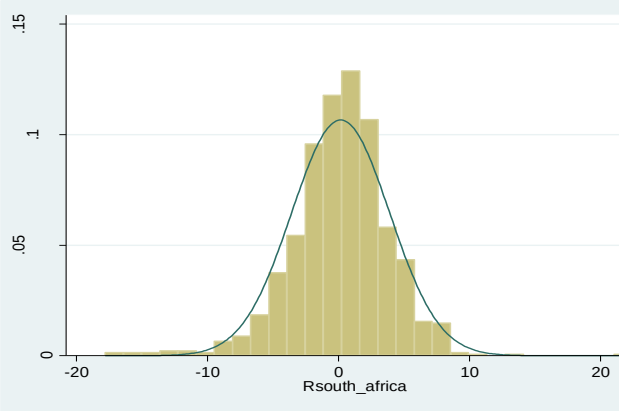

Figure4. 26 normal probability plot of south africa

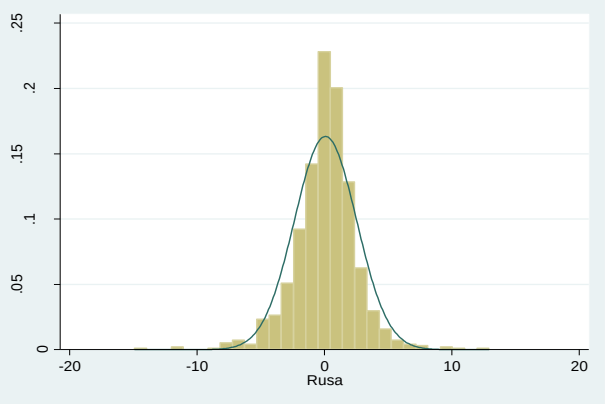

Figure4. 28 normal probability plot of USA

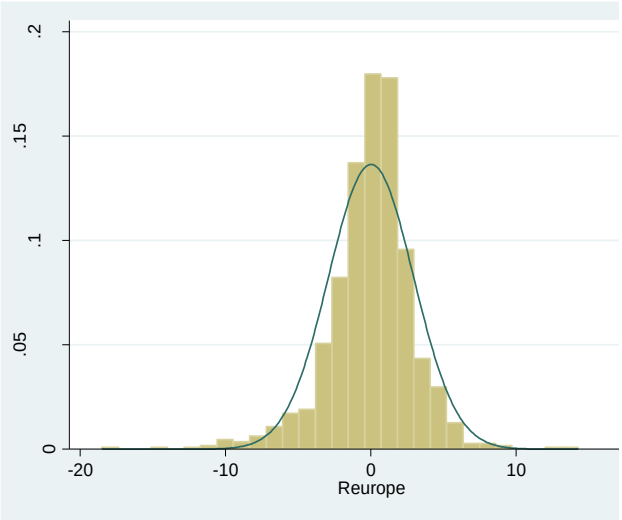

Figure 4.29 normal probability plot of Europe

var Rusa Rnigeria Rusdollar, lags(1/3)

Vector autoregression

Sample: 1999w5 - 2017w46, but with gaps Number of obs =958

Log likelihood = -6245.758 AIC = 13.10179

FPE = 98.31369HQIC = 13.15981

Det(Sigma_ml) = 92.3449 SBIC = 13.25414

Table4.11 estimated VAR model (USA, Nigeria, us dollar)

	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Rusa						
L1.	-.1329896	.0324671	-4.10	0.000	.1966239	-.0693553
L2.	.0050569	.0328648	0.15	0.878	.0593569	.0694708
L3.	.0663555	.0323777	2.05	0.040	.0028964	.1298145
Rnigeria						
L1.	.040473	.021445	1.89	0.059	.0015585	.0825044
L2.	-.018751	.0211114	-0.89	0.374	.0601286	.0226266
L3.	-.010636	.0210855	-0.500	.614	.0519628	.0306908
Rusdollar						
L1.	-.0166486	.0693488	-0.24	0.810	.1525698	.1192726
L2.	.0641884	.0696961	0.92	0.357	.0724135	.2007903
L3.	-.1016769	.0699917	-1.45	0.146	.2388581	.0355043
_cons	.0796554	.0776549	1.03	0.305	.0725454	.2318561
Rnigeria						
Rusa						
L1.	.1327214	.0487181	2.72	0.006	.0372358	.2282071
L2.	.1214805	.0493149	2.46	0.014	.0248251	.2181359
L3.	.0179573	.0485839	0.37	0.712	.0772655	.11318
Rnigeria						
L1.	-.0217893	.0321791	-0.68	0.498	.0848591	.0412805
L2.	.1092586	.0316785	3.45	0.001	.0471699	.1713473
L3.	.0093654	.0316396	0.30	0.767	-.052647	.0713779
Rusdollar						
L1.	-.2930644	.1040606	-2.82	0.005	.4970194	-.0891095
L2.	-.2684021	.1045817	-2.57	0.010	.4733785	-.0634257
L3.	-.0472089	.1050252	-0.45	0.653	.2530546	.1586367
_cons	.0243399	.1165241	0.21	0.835	.2040432	.252723
Rusdollar						
Rusa						
L1.	-.0108886	.0152257	-0.72	0.475	.0407304	.0189532
L2.	-.0116062	.0154122	-0.75	0.451	.0418136	.0186012
L3.	-.0098704	.0151838	-0.65	0.516	.0396301	.0198892
Rnigeria						
L1.	-.006572	.0100568	-0.65	0.513	-.026283	.013139
L2.	-.0037605	.0099004	-0.38	0.704	.0231649	.0156438
L3.	.0081829	.0098882	0.83	0.408	.0111977	.0275634
Rusdollar						
L1.	.0241225	.0325217	0.74	0.458	.0396189	.0878638
L2.	-.0000612	.0326846	-0.00	0.999	.0641218	.0639993
L3.	-.0223493	.0328232	-0.68	0.496	.0866815	.0419829
_cons	.0020604	.0364169	0.06	0.955	.0693153	.0734362

. var Reurope Rnigeria Rusdollar, lags(1/3)

Vector autoregression

Sample: 1999w5 - 2017w46, but with gaps Number of obs =958

Log likelihood = -6333.554 AIC = 13.28508

FPE = 118.0907HQIC = 13.3431

Det(Sigma_ml) = 110.9212 SBIC = 13.43743

Equation	Parms	RMSE	R-sq	chi2	P>chi2
Reurope	10	2.90221	0.0262	25.76291	0.0022
Rnigeria	10	3.59505	0.0579	58.87898	0.0000
Rusdollar	10	1.13006	0.0050	4.826451	0.8492

Table4. 12 estimated VAR(europe,nigeria us dollar)

	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Reurope						
L1.	-.1061802	.0354134	-3.00	0.003	.1755893	-.0367711
L2.	-.0181987	.0358465	-0.51	0.612	.0884566	.0520591
L3.	.050537	.0356304	1.42	0.156	.0192972	.1203713
Rnigeria						
L1.	.070213	.0259982	2.70	0.007	.0192575	.1211685
L2.	-.0249187	.0256003	-0.97	0.330	.0750944	.0252569
L3.	-.0597831	.025402	-2.35	0.019	.1095701	-.0099961
Rusdollar						
L1.	-.1146037	.0912736	-1.26	0.209	.2934967	.0642892
L2.	.0643062	.0913593	0.70	0.482	.1147547	.2433671
L3.	-.0209451	.0914391	-0.23	0.819	.2001624	.1582723
_cons	.0284844	.0933193	0.31	0.760	-.154418	.2113867
Rnigeria						
Reurope						
L1.	.1883861	.0438676	4.29	0.000	.1024073	.274365
L2.	.1232809	.044404	2.78	0.005	.0362507	.2103111
L3.	-.008916	.0441363	-0.20	0.840	.0954215	.0775895
Rnigeria						
L1.	-.0251951	.0322046	-0.78	0.434	-.088315	.0379248
L2.	.1061259	.0317118	3.35	0.001	.043972.1682798	
L3.	.011696	.0314661	0.37	0.710	.0499764	.0733685
Rusdollar						

L1.	-.1350704	.113063	-1.19	0.232	.3566698	.086529
L2.	-.1686399	.1131692	-1.49	0.136	.3904474	.0531675
L3.	-.075615	.113268	-0.67	0.504	.2976163	.1463863
_cons	.0522669	.115597	0.45	0.651	-.174299	.2788329
Rusdollar						
Reurope						
L1.	-.0018086	.0137892	-0.13	0.896	-.028835	.0252178
L2.	-.015987	.0139579	-1.15	0.252	.0433439	.0113699
L3.	-.0164924	.0138737	-1.19	0.235	.0436843	.0106996
Rnigeria						
L1.	-.0049693	.0101231	-0.49	0.624	.0248103	.0148717
L2.	-.0031842	.0099682	-0.32	0.749	.0227216	.0163531
L3.	.008987	.009891	0.91	0.364	-.010399	.028373
Rusdollar						
L1.	.0239012	.03554	0.67	0.501	.0457559	.0935583
L2.	-.0134319	.0355734	-0.3	0.706	.0831543	.0562906
L3.	-.0375423	.0356044	-1.05	0.292	.1073257	.0322411
_cons	.0004383	.0363365	0.01	0.990	-.07078	.0716565

APPENDIX B

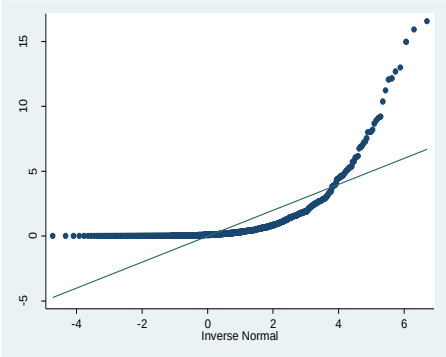

Figure4. 30 q-q normality plot of squared standardized residuals MOR

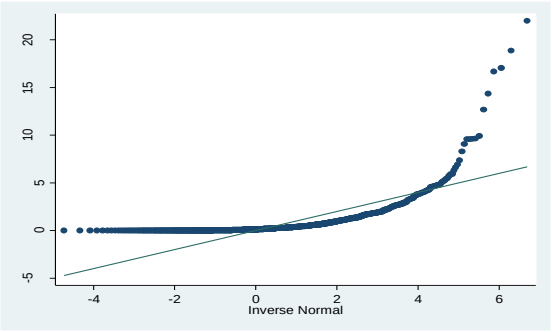

Figure 4.31 q-q normality plot of squared standardized residuals SA

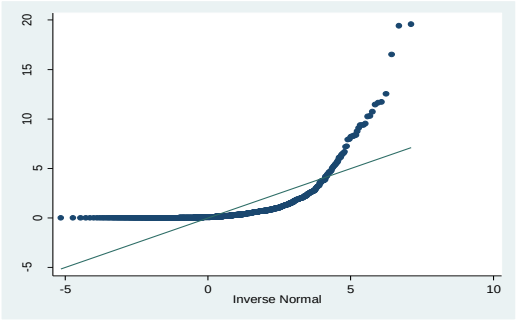

Figure 4.32q-q normality plot of squared standardized residuals KEN

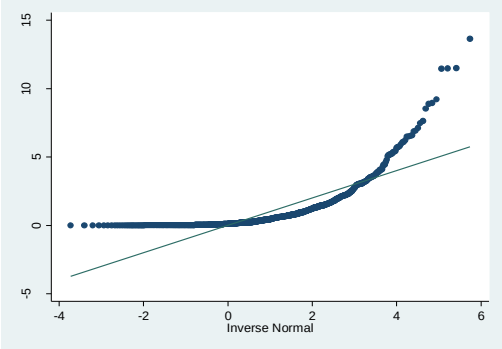

Figure 4.33q-q normality plot of squared standardized residuals USD

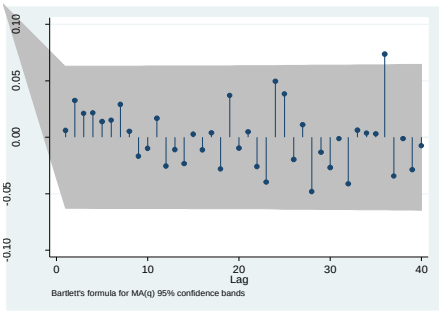

Figure 4.35 correlogram plot squared residuals USA

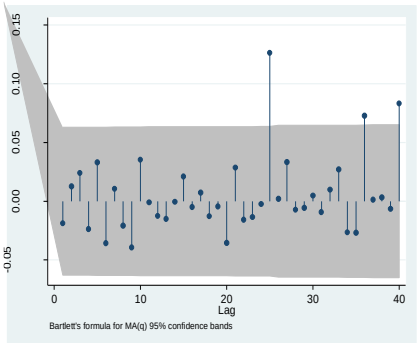

Figure 4.34correlogram plot squared residuals EU