Dynamic Linkage amongst Oil, Gold, Exchange Rates and Stock Markets in Africa: Evidence from Volatility of Major African Economies

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DECLARATION

I declare that **Dynamic Linkage amongst Oil, Gold, Exchange Rates and Stock Markets in Africa: Evidence from Volatility of Major African Economies** is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

I further declare that I submitted the dissertation to originality checking software and that it falls within the accepted requirements for originality.

I further declare that I have not previously submitted this work, or part of it, for examination at Unisa for another qualification or at any other higher education institution.

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Abstract

The premise of this study is that price fluctuations amongst exchange rates, stock and commodities markets are dynamically linked. The study models monthly price changes amongst these markets in 20 highest World Bank GDP ranked African economies between the years 2000 and 2019 using a copula based DCC GARCH framework. The results show that, there is a time varying co-movement amongst these markets that tend to increase during times of turbulence in sampled markets. Dynamic relations are found to be quantitatively and relatively substantial for economies of Egypt, South Africa, Tanzania, Libya and Zambia. The study also finds a relatively high bivariate association amongst currencies mainly the South African rand, Botswana pula, Moroccan dirham, CFA franc and Tunisian dinar.

Key words: Stock markets**,** exchange rates, crude oil, gold**,** co-movement, copula, DCC GARCH, GJR, exponential GARCH, commodities.

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1 Introduction

1.1 Background of Study

Levels of price volatility in a market exposes all participants to conditional uncertainties due to causal, interdependent and consequential spill-over effects from price shocks. In the commodities markets, both high and low volatility in the price exposes participants to various conditional risks that can be influential to pertinent economic growth drivers, given the level of participants' exposure to commodities. The commodity related risk exposure is also experienced by other commodities that interact with or depend on one another in varying instances, such as cases when they are complements, substitutes or supply chain additives. Depending on the micro and macro-economic level of dependence, demand and availability, crude oil and gold are examples of commodities whose price shocks have been shown to have a relationship with each other and also with economic variables such as exchange rates, stock markets, remittances, employment and inflation (Baur and McDermott, 2010; Arouri, Jouini and Nguyen, 2012; Ciner, Gurdgiev and Lucey, 2013; Hou et al., 2015; Raza et al., 2016; Akçay and Karasoy, 2019) . Researchers have shown how, for an example, two distinct price plunges in the nominal price of crude oil that took place between periods of 2008 to 2009 and 2014 to 2016 had an impact on economic growth in economies such as those in the sub-Saharan African regions (SSA) and oil net-exporting economies Angola, Nigeria, República Bolivariana, Russia, United Arab Emirates , South Sudan, Chad and Venezuela. The two price oscillations influenced an annual average 73% decrease in GDP growth for the SSA economies between 2014 and 2016 and impacted economic activity measures such as economic growth, foreign investment, real currency, foreign exchange reserves and real income during and post oil price plunge period for the oil exporters (Olakojo, 2015; World Bank Group, 2018). On a microeconomic level, the oil price plunge globally affected expenses, profits and hence stock prices of firms in oil sensitive sectors such as those in resources, manufacturing, logistics and transport. From the end of 2016 and beginning of 2017, oil prices started increasing and firms such as those in the previously mentioned sectors experienced higher expenses that were or would have been eventually passed to consumers and hence impact inflation and affect stock prices due to altered profits. The relative commodity price fluctuation impacts can also be driven by the originating forces that are causal to a particular price shock, an example is the resulting impact from the 2014 to 2016 oil price shock that was driven by oil supply shocks and geopolitical events while that of 2008 – 2009 occurred as a result of and in tandem with the global financial crises (Filis, Degiannakis and Floros, 2011; Wang, Wu and Yang, 2013; Bank, 2018). Deaton (1999) argues that, depending on the level or ratio of commodity exports to GDP, a change in the price of a commodity can induce change to economic growth. Hence, exports' diversification and concentration levels pose a potential risk to an economy due to possible adverse price oscillations.

Crude oil is an example of a commodity that can potentially affect economic growth. This effect is different for economies exporting and importing a commodity both on a macro level and for sectors depending on it as an input, output, substitute or complement, on a micro level. The impact commodities have on economic growth creates a level dependence for an economy or industry that is amplified by distinct factors such as rates of decay and renewal, price trends, acquiring or selling denomination, economic shocks, supply, demand, investment, production dependence, diversity, income, and overall economic policies (Deaton, 1999; World Bank Group, 2018). In each economy, commodities are either sufficiently available and the surplus hoarded or exported; or insufficient and imported due to the mismatch in their demand and availability. For a commodity exporting economy, aggregate supply elasticity can be observed in the levels of exported quantity and on changes in measures such as domestic current account, trade terms, real and nominal exchange rates. Keeping other factors constant, for a country importing a commodity, the nominal exchange rate quotation of the domestic currency has an income and price demand elasticity effect that are based on the commodity the country can purchase in the absence of substitutes and this adds a certain weight to the budget and current account, given the level of income allocated and reliance on the commodity. Commodity importing economies and commodity sensitive sectors also have their inflation, foreseeable growth and firm revenues affected if the commodity is a vital input. On a macroeconomic level, an example of an imported commodity impact on economic activity can be observed using the case of high oil net-importers, India and Tanzania in the period between 2014 and 2015, where crude oil price declines were attributed to some of the economic improvement cited in the value of oil imported and hence their account deficit (Hou et al., 2015). On a micro level, dependence of a sectors' cash-flow sensitivity to commodities, domestic industries' concentration, size and competition; could mean that changes in the price of a commodity can conditionally alter the value of stocks in an economy. These factors are however an issue more on developing countries that still have less diversified economies as developed economies are generally more diversified and have the ability to stabilise their economy's returns even when commodities experience adverse price fluctuations that affect some commodity sensitive sectors (Milani, 2011; Arouri, Jouini and Nguyen, 2012). Degiannakis, Filis and Arora (2017) argue using a cash flow based stock valuation model that discount rates, internal in the model, are also affected by commodities such as oil and hence impact the present value of stocks in a market. The Fisher equation becomes the base of their argument that discount rates take into consideration expected inflation and real interest rates. Holding other factors constant, when production costs change due to change in oil price, the value of the price change is passed to consumers which may alter expected inflation resulting in a change in the discount rate and hence stock value.

Transmission effects between commodities such as oil and stock markets have been shown to be unidirectional from oil shocks to equities markets and the strength of the conveyed asymmetric spill-over tends to be sensitive towards an industry's dependence on a commodity as either an input or output (Arouri, Jouini and Nguyen, 2012; Degiannakis, Filis and Floros, 2013; Behmiri and Manera, 2015). Within financial markets, gold is another commodity that has been shown to offer an alternative investment class and as having the ability to store financial value by providing a hedge against inflation and inverse leverage impact (Behmiri and Manera, 2015). The metal's ability to store value allows it, as an asset class, to have conditional hedging qualities that can offset losses experienced due to its varying dependence relation with several asset classes. This capability and phenomenon by gold has been observed to have positive impact in the stock markets of large emerging economies and exchange rates in developed markets (Baur and McDermott, 2010; Ciner, Gurdgiev and Lucey, 2013; Reboredo, 2013; Raza et al., 2016). Gold also has a high industrial and jewellery usage and is also part of foreign exchange reserves held by most central banks to provide protection, confidence and stability for their domestic currency. Gold's inverse relation to some currencies, enables it to provide a hedge against currency related economic fluctuations and hence allows central banks to hedge against various risks that could emanate from economic activities that require interactions with foreign exchange rate markets and this is due to gold's predominant pricing in a stable currency, the United States of America's dollar (Joy, 2011). Open economies that adopt none or a nearly nonefloating exchange rate management system (EMS) intervene in the currency markets to minimise exchange rate related risk and hence try to circumvent unexpected adverse effects of their currency's movement. The interventions from open economies' central banks using methods such as trading foreign and domestic reserves, currency trade restrictions and various interest rates adjustments; aim to offer an alternative money demand and supply equilibrium.

The ease at which the demand and supply of currency flows inter- and intra-economies also determines the level of foreign direct investment (and disinvestment) by those taking advantage of various economic differentials to improve their economic participation, with other factors held constant. The flow of foreign and domestic capital amongst economic agents will induce change on an economy's real exchange rate as it alters the currency's supply and demand equilibrium, with other factors held constant. The change in an economy's effective exchange rate imposes or is caused by changes in the stock market of an economy (De Gooijer and Sivarajasingham, 2008; Zhao, 2010; Alagidede, Panagiotidis and Zhang, 2011; Bessler, Kolari and Maung, 2011; Nguyen and Bhatti, 2012; Chkili and Khuong, 2014; Moore and Wang, 2014). The direction of causation between currency and equity markets varies for economies. Theoretically, the "flow-oriented" and "stock-oriented" models suggest a contradicting direction of causation that relate an economy's currency to its stock market. The "flow-oriented" model suggests that, changes in exchange rates affect an economy's stock market through changes emanating from relative price and demand for domestic goods arising from international trade and competitiveness. International competitiveness impacts economic output, income and investment decisions that pertain to future cash flows, affecting the present value of stock prices (Dornbusch and Fischer, 1980). The "stock-oriented" model suggests that trading activities in the equities market affect the wealth of individuals who timeously balance their portfolios and stock holdings by changing their demand for means to transact and trade globally, such as financial assets in the form of money. The resulting change in money supply and demand equilibrium affects interest rates, hence allowing for misalignment in exchange rates markets (Branson, 1981; Frankel, 1983). Some developing economies have chosen currency regimes, management and policies that deliberately avoid the appreciation of their currencies and allow their currencies to be misaligned. These economies view their policies as an avoidance and a discouraging measure taken to prevent having a perceived overvalued currency that can negatively impact economic growth. Though the relationship between real exchange rate misalignment and economic growth exists, there are certain optimal real exchange rate (RER) threshold levels at which undervaluing or overvaluing a currency can be associated with either positive or negative economic growth and can directly affect the stock market (Elbadawi, Kaltani and Soto, 2012; Yan and Yang, 2012; Couharde and Sallenave, 2013; Oreiro and Araujo, 2013; Tang, 2015). Moore and Wang (2014) also argue that the relationship between stock market and exchange rate returns is both dynamic and time varying for developed and developing economies. Stock markets have been shown by researchers, such as Enisan and Olufisayo (2009), to have an influence on economic growth as they act as enablers and regulators to efficient allocation of financial resources and also assist in the lowering of market participant's uncertainties and costs. Ideally, if an economy's stock market has a certain level of transmission effect to domestic (or foreign) exchange rate markets or vice versa, manoeuvring (or predicting) adverse market shocks may require adjusting (or observing) the other to circumvent and invert shocks faced by or from the other market. Both exchange rate and stock markets have been found to be influenced by commodity markets. Researchers such as Jain and Biswal (2016) extend the idea of shocks in the prices of commodities influencing stock and exchange rate markets by showing that the relationship is dynamic. Oil and gold have together been studied and shown to have a dynamic volatility structure that shows their dependence and influence towards other commodities, equity and currency markets (Chkili, 2016; Raza et al., 2016; Xu et al., 2019)

Whether an economy is a commodity net-exporter or net-importer the exchange rate management system (EMS) adopted by an economy, level of public debt, commodity trading policies, trade terms, costs and economic openness are some of the crucial factors that allow the discussed relations to hold; as they dictate the manner in which the commodities can be traded cross borders. For open economies, economic determinant factors such as inflation, exchange rate misalignment, consumption, productivity, foreign asset reserves, policy regimes and trade terms; have over the years increased the reliance of a country or region's economic growth on the level of interaction it has with the global markets. Economic and markets interdependence expose both commodity exporting and importing economies to varying levels of conditional and unconditional risks and an example of the conditional risks is the availability of goods or commodities consumed by an economy, their price and the resulting spill-over effect of their markets' interaction. This study will use a dynamic conditional correlation multivariate copula GARCH approach to study whether there is a possibility of dynamic influential and dependence relationship amongst gold, oil, exchange rates and stock exchanges for major African economies.

1.2 Motivation and Objective of Study

Several African economies are becoming noticeable emerging economic participants in the global markets as their infrastructures, stock markets, and general economies mature and align to global standards and openness. Hence, the studying of time varying correlation structures and influence amongst influential asset classes will offer insights on informational dependence and potential spill-overs that may occur and require policy and investment decision repositioning. The objective is to study the time varying correlation structure and dependence of the sampled asset classes using the highest World Bank GDP ranked African economies of Algeria, Angola, Botswana, Cameroon, Democratic Republic of Congo, Côte d'Ivoire (Ivory Coast), Arab Republic of Egypt, Ethiopia, Gabon, Ghana, Kenya, Libya, Morocco, Nigeria, South Africa, Sudan, Tanzania, Tunisia, Uganda and Zambia. The study is motivated by the limited availability of research that is not country or region specific and aims at focusing on offering insights on the relationship of the sampled variables for relatively small economies with high levels of commodity exports.

1.3 Purpose and Significance of Study

At primary or secondary refined stages, commodities such as oil, diamonds, coal, nuclear, hydro or wind, gold, gas, cocoa, cotton and sugar have a demand for raw usage or as inputs in production processes of various by-products. This dissertation aims to add to the existing understanding in the dynamic relationship amongst commodities, exchange rates and stock markets. The results from the studied relationship will offer broader insights on the impact commodity prices have on economic (agents') shocks especially for the lesser studied African economies that are price takers as most of the commodities they export are regionally quoted at varying currencies but traded and priced across national borders by referencing relatively well globally traded and stable currencies such as the United States dollar, Pound Sterling and European Monetary System's Euro. Studying commodities exported by African countries, Deaton (1999) argues that there exists a link between economic shocks and commodity demand, supply and hence their prices. The research also underscored the importance of commodity prices on overall exports, emphasizing that, if exports are a crucial part of an economy's income, changes in their overall value and price can impact an economy through various economic channels. For exports-driven economies, export price change hence becomes a critical lens through which to assess existing and potential economic risk.

Within the African continent countries such as Eritrea (copper), Nigeria (oil), Angola (oil), Mali (gold), Burkina Faso (gold), Chad (oil) and Guinea-Bissau (cashew nuts), are examples of cases where exported commodities (mentioned in brackets) account for a large portion of an economy's total exports, fitting the description of commodity driven currencies or economies, a term defined by Rogoff and Chen (2003) when analysing commodity driven countries of Canada, Australia and New Zealand. The broader view is that, impact of commodity price shocks within the African continent especially for countries such as those mentioned above, should be studied as they may pose risk to Africa's economic growth (Deaton, 1999). Also, the value derived from these commodities also allow governments to extract revenue and are in some instances used as a source of foreign currency. Hence, the market defined real prices of commodities dictate the way commodities can be traded across borders, holding other factors constant. The results and findings in the study show that both the local currencies and stock markets in most of the sampled economies show a dynamic dependence that is on average positive to the prices of the sampled commodities. An implication that could be of importance to regulators such as central banks, policy makers including governments and risk averse money managers since it means that the fluctuation of prices in the commodities' market has an impact on financial markets and that this impact is dynamic. Hence, in the African continent, changes in the commodities market could be directly linked to resulting changes in parts of the financial markets and this could have varying detrimental (and some cases positive) social effects.

1.4 Problem Statement

From the background discussion, this dissertation aims to study whether there is a dynamic linkage, correlation structure and dependence amongst the markets of oil, exchange rates, financial stocks and gold. The relation may also be distinguished for cases where the sampled commodities are exported or imported. The relationship each commodity has per sampled economy is studied using a copula based multivariate vector autoregressive generalized autoregressive conditional heteroscedasticity (GARCH) approach which will allow viewing of time varying correlation and dependence over the sampled period.

1.5 Hypothesis of Study

To reach its objectives and significance, the study will test the following:

- If there was leverage effect observable in the prices of commodities and financial market variables over the period

- If, for the sampled African countries, there is a time varying dependence relationship amongst price innovations of local exchange rate, local stock market with crude oil and gold.

- If there is a feedback causal conditional relationship amongst commodities, stock and exchange rate markets.

1.6 Limitations of Study

This study uses scaled returns data, which is not at price level and hence, the findings must be taken with caution that the relation is based on logarithm changes and not at actual price levels. This study also uses multivariate analysis methodologies but does not account for potential leverage effect at varying regimes. Leverage effect defined, parameterised, conditioned or considered at varying regimes and market conditions can indicate whether for any of the sampled markets a relatively significant negative price shock or volatility has more, less or similar economic impact to that of a positive shock in a regime. The GARCH-stylised models applied in this study, like most ARCH-type models, do not cater for asymmetry in the return series. In this dissertation, the role of external significant unpredictable events and outliers such as geo-political and natural phenomenon are not included as dummy variables though they might have been influential in parts of the sampled period and have been noted by researchers to be influential towards endogenous variables' volatility and forecasts (Behmiri and Manera, 2015). Nominal instead of real exchange rate value of the USA dollar is used as an anchor or conversion currency; this could mean that there is no insulation in the data used from USA economic fluctuations.

No statistical tests, such as those offered in principal component or factor analysis were conducted to define variables nor to sample the economies analysed and the timeline hence the findings are conditional. Researchers such as Sakemoto (2018) have mentioned how bonds and other markets (which are not sampled by this study) have observable influence towards some sampled markets such as the equities markets.

During the sampled period, there is and has been a significant change in the use of technology (e.g. digital currency) and renewable energy, that may, through various synergies, somehow shift the dynamics and findings on how the sampled variables are treated (and react in the future) per sampled economy. Input substitutions, exploration and potential discoveries of reserve commodities can change how each economy sampled is categorised in this study from a net-exporter-importer perspective. Only end of period or month dollar prices are used in this study to convert relative currencies; as African nations embrace open boarder policies; this can significantly change the way deductions are made regarding future currency shocks in the predominantly dollar priced sampled variables. No factor is included to cater for interdependence amongst sampled economies as there can be significant bilateral trades that cause market cross-border effect between economies.

1.7 Organisation of Study

The continuing structure of this study presents the work previously done in relation to this field and topic in the form of a literature review in the second chapter. The third chapter introduces the econometric model and the theory that underpins the model. The fourth chapter initially introduces the data and offers an analysis on it based on the methodologies that are discussed in the third chapter. The fifth and concluding chapter gives an overall view of this dissertation and potential future research.

2 Literature Review

2.1 Introduction

The change in the value and price of commodities has been discussed in Chapter 1 and how it has financial implications on economic variables that are pertinent to economic performance. The subsequent, consequential and dynamic resulting financial leakage amongst economic variables such as stock markets, exchange rates and commodity price changes; differs for economies and depends on the drivers of demand for and domestic availability of pertinent commodities per economy, especially for developing economies. This chapter aims to outline, evaluate and give insights on previous empirical research that has contributed in highlighting the ensuing effects from the linkage amongst commodity price shocks, exchange rates and stock markets.

2.2 Co-movement of Prices in the Commodities Markets

Co-movements of prices in the commodities markets, like non-normality and heteroscedasticity, is regarded as a salient stylised fact that should be considered when studying the commodities' market. Co-movement, should it exist for unrelated commodities, is critical as it would mean that fundamental market observations and concepts can be easily disregarded as the movement in one (or a few) commodities could determine a market shift or trend in the direction determined by a market sample and this would require a specific approach that should account for its existence. Co-movement in substitutes, complements, production inputs or any form of related commodities is well expected as they are to react and move somehow jointly to certain shocks. Effects of unsystematic macroeconomic and noneconomic shocks such as geopolitical events, weather, wars and global disease outbreaks can be attributed to this phenomenon, where global events impasse common responses in markets and hence prices are expected to correlate and move in tandem during such episodes.

There is empirical research that has tested the hypotheses of co-movements in the price of unrelated commodities and attributed the impact to be from (and cause) business trends and fluctuations. Researchers have over time applied varying frameworks to mitigate model risk, sample period biasness, robustness in the choice and distinctness of sampled commodities and account for relatively common inputs from global shocks. Pindyck and Rotemberg (1990) offer a seminal argument for the existence of excess co-movement (ECM) of commodity prices by studying monthly price data (from 1960 - 1985) of seven commodities that are regarded as unrelated namely cocoa, copper, cotton, crude oil, gold, lumber and wheat. The research makes use of normality and ordinary least square (OLS) assumptions, latent variable based models are used to study macroeconomic variables such as exchange rates, inflation, stock market and money supply; that are included as exogenous predictors. The paper makes a conclusion of ECM based on the explained variation (r-squared) that is observed when including commodities in the linear regression model and proposes that the length of sampled period as one of the factors that are pertinent towards influencing an ECM conclusion in commodity prices.

Partha, Trivedi and Varangis (1996) use a GARCH type framework to test the zero ECM hypothesis on unrelated commodities that are grouped on possible regional and industrial production and usage. Their test extends the study period of Pindyck and Rotemberg (1990) by adding a sample period of 1974 – 1992, to the original 1960 -1985, that is used to check for sample period biasness. The research, based on multivariate Engle-Kroner GARCH model, finds only weak evidence of ECM but suggests there are possibilities when univariate GARCH models are applied. Deaton (1999) by sampling African economies' 26 primary commodities, argues against the existence of excess co-movement hypothesis (ECM) especially for unrelated commodities. The research argues that supply and demand conditions are unique per commodity and hence global shocks would affect each commodity uniquely based on its importance, availability, supply and level of consumption. Instead of conforming, the paper argues that there is rarely an upward trend in commodity prices, such that most have long run real price reversions and high autocorrelation. Cashin, McDermott and Scott (2002) study 36 commodities' monthly data from January 1957 to August 1999 and define market periods (booms and slumps) based on peaks and troughs defined from a revised version of the Bry–Boschan algorithm, which is used to periodically subdivide a time-series dataset into sub-periods, and in their paper used to get periods of booms and slumps. The research shows most commodities as being skewed and leptokurtosis hence deviating from normality. The study also shows that, for a few (5 of the 36 commodities) , most have slump price periods that are longer than boom price periods, highlighting how oil and gold prices move in tandem but in general dispute any level of significance in (Spearman-rank) correlation for the movement of prices between commodities. The Spearman-rank correlation test is performed, and found to be insignificant, between a market period and its duration i.e. a slump and the duration of a slump. The research disputes that levels in correlation can be used as evidence to the existence of ECM as they are low for unrelated commodities.

Though the relation amongst commodities has been shown and contradicted, crude oil seems to have impact in influencing price movements in the commodities markets. Ncube, Tessema and Gurara (2014) argue that ECM exists or is stable in periods when there is high probability of a recession or market slumps and that economic variables and their fundamentals are sufficient in explaining commodity price fluctuations. Their research uses I-GARCH and BEEK-GARCH models to argue against the existence of ECM, which is anticipated in the conditional covariance structure of the residuals applied in the MGARCH models. Though the research bases it conclusions on pair-wise tests, it is arguable that adding a third variable to the pair can also produce similar conclusions and is quite a limiting view of conditional asset behaviour.

Crude oil and some macroeconomic exogenous variables are critical input factors when studying price behaviour in the commodities markets. Behmiri and Manera (2015) show the critical role exogenous factors such as natural disasters, wars and oil prices play in the price movements of various metals in the commodities markets. Their study detects and cleanses data from outliers but use for analysis, both original and outlier-insulated data to make inferences that are based on generalised additive outliers GARCH and Glosten, Jagannathan and Runkle GARCH models to capture data asymmetric reaction from oil prices. The research finds that the altered data (that is free from significantly tested outliers) showed modelling improvement when it is assessed using factors such as excess kurtosis and skewness. The results of the research also show ambiguous non-uniform impact from oil price fluctuations towards metals such as gold, where negative oil prices changes are shown to decrease the price of gold. The study consists of daily closing prices of Brent crude and a sample of 10 commodities or metals traded in the London Metal Exchange (LME) from July

1993 to January 2014. The metals sampled include aluminium, copper, lead, gold, silver, platinum, palladium, nickel, tin and zinc.

2.3 Commodity Markets' Influence on Economic Activity

The expenditure approach to measuring economic activity, in the form of gross domestic product (GDP), attaches economic performance to an economy's expenditure on government purchases, imports, exports, consumption and investment. Hence, for a commodity trading open economy, variables discussed sections 1.1 and 2.2 such as terms of trade, market value, quoted price will have influence how economies and firms interact in domestic, foreign, goods, services, factors and financial markets and how they drive economic growth. Main economic growth drivers are distinguishable for developed and developing economies. For developed economies, physical human capital, technology, policy framework, research and skill development (through specialisation and innovation) are all crucial determinants of economic growth. Whereas factors such as level of natural resources, indebtedness, inflation, pursued policy framework, power supply, (foreign) direct investment (FDI), economic openness and educational investment are all associated with being vital for economic growth for developing economies (Petrakos and Arvanitidis, 2008; Barnebeck and Dalgaard, 2013; Hossain and Mitra, 2013; Asiedu, 2015; Bittencourt, Eyden and Seleteng, 2015; Chirwa and Odhiambo, 2016). Economic growth determinants can also depend on non-uniform underlying factors that affect both developed and developing economies alike, such as the commodities adopted by an economy as sources of energy (Arouri et al., 2014; Bhattacharya et al., 2016). There is a notable relationship between an economy's growth and development level to its energy demand for consumption in sectors such as industrial production, transportation, commercial and residential (Bhattacharya et al., 2016). Economic shocks, channelled through these key economic growth drivers, have a dynamic impact on an economy's exports, imports, exchange rates and stock markets through channels such as inflation, production costs and terms of trade.

Researchers have studied channels and agents through which commodity price shocks relate to stock and exchange rates markets. The core premise that has fuelled these research ideologies have focused on rationalising the impact of commodity price movements on both equity and currency markets (Sujit and Kumar, 2011). There is vast empirical evidence that has disputed and confirmed existing theory and expectations about commodity prices' impact on economic variables and hence its activity. In cases where an influential relationship exists, much of the neutral, contradicting and mostly conforming empirical studies differ on how commodities impact an economy especially in conditional cases where they are imported or exported by the economy or industry being empirically studied. Researchers have shown none-consistent findings in their studies, these inconsistencies arise mainly from varying sampled economies, chosen research periods and methodologies. The ensuing subchapter presents empirical studies that show the influence commodities receive and impasse to economic variables.

2.3.1 Empirical Evidence of Dynamic Influence amongst Gold, Oil, Currency and Stock Markets

Researchers such as Ahmed and Huo (2020) have studied the impact of commodities in the financial markets of Botswana, Egypt, Ghana, Kenya, Morocco, Namibia, Nigeria, South Africa, Tunisia, Zambia and indirectly, member economies of the regional BRVM stock exchange. The study uses daily prices of crude oil and each economy's domestic foreign exchange and stock markets as proxies of the commodity and financial markets, respectively. The prices are sampled from 3 January 2007 to 30 December 2016 and a VAR-BEKK-GARCH model is used to study the dynamic spill-over impact amongst the markets. The study finds interactions of the markets that seem to be structural per country because the results are not consistent. For instance, increase in the returns of crude oil are shown to positively influence the currencies of Botswana, Nigeria and Zambia but negatively impact Egypt's currency. Since the study uses oil as an endogenous variable, influence from currency markets of Kenya, Morocco and BRVM; and the stock market of Namibia, to crude oil is highlighted. Volatility spill-over effects between oil and exchange rate markets are found to be significant for eight of the sampled economies while a unidirectional transmission from crude oil to stock markets is reported for Egypt, Ghana, Namibia, Nigeria, and Zambia. The volatility transmissions between exchange rate and stock markets is found from stock markets to exchange rates for Tunisia, Kenya and South Africa, and from exchange rates to stock markets for Botswana, Kenya, Morocco and Zambia and. The study further proposes an optimal asset allocation strategy that investors seeking to hedge a portfolio consisting of the sampled variables can use.

Research by Zankawah and Stewart (2019) also focuses on the impact oil prices have on the Ghanaian financial markets using the cedi-USA dollar exchange rate and Ghana Stock Exchange (GSE) as proxies. Included in the study is the USA's Standard and Poor 500 (S&P) index used to assess the impact of external market influence. BEKK- GARCH and its restriction-imposed version, the triangular BEKK-GARCH models are used for comparing between using crude oil as an endogenous or exogenous variable in the assessment. The comparison is based on a priori that macro-economic variables of an economy like Ghana cannot possibly influence the global crude oil market due to factors such as its size, production and importing capability. Regardless of how the crude oil input variable is treated, it is found to have an asymmetric transmission to the foreign exchange markets of Ghana. However, for the GSE-crude oil nexus, when oil is endogenous it does not have a significant impact towards the GSE, and this fact does not hold in the model that treats oil as exogenous. Due to the negative impact oil has towards the cedi, researchers suggest currency futures or forward markets as being useful in hedging against adverse movements in the oil markets. The study also highlights the unidirectional impact of crude oil to the S&P 500 index.

Xu et al. (2019) use high-frequency (five-minutes interval or frequency) intra-day data spanning 4 January 2007 and 28 April 2016 from China and United States of America (USA) to study time-varying and asymmetric volatility spill-overs between oil and stock markets. For stock market and oil proxies, the study respectively uses China's Shanghai Composite and USA's Standard and Poor 500 (S&P) indices and West Texas Intermediate (WTI) future prices with one-month maturity. The research defines bad and good volatility spill-overs that are based on negative and positive shocks, respectively. The study finds the existence of time varying asymmetric volatility spill-overs (and interdependence) between the sampled markets that are mainly observed to be from bad (relative to good) volatility spill-overs. In this study, realised volatility (RV) is defined as the sum of squared intra-day returns. RV is then decomposed into positive realised semi-variance and negative realised semi-variance, from positive and negative shocks, respectively, and are used to estimate good and bad volatility spill overs and assist in the analysis of asymmetry from a VAR's forecast error decomposition perspective.

Adewuyi, Awodumi and Abodunde (2019) use monthly data from June 2002 to May 2017 to study the influence of gold on the stock markets of South Africa and Nigeria using VARMA-BEKK-AGARCH and quantile regression models. Included as variables in the study are prices of gold, oil, South Africa's JSE all share index, Nigeria's NSE all share index, S&P's SPX volatility index and treasury bills for both economies. The study compares results between cases when structural breaks are applied and cases when they are not considered, to infer cross-market shock impact between markets. The study finds that there is evidence of impact within gold and the stock market of Nigeria regardless of structural break consideration, but this is only true for South Africa in the absence of structural breaks. Gold is also found to have a feedback influence with the South African stock market but not that of Nigeria. The research also mentions that based on the relationship each economy's stock market has with gold, its inclusion in a portfolio can be a useful hedge for Nigerian stock market but not for the South African stock market.

Blau (2018) studies and find volatility spill-over effects between exchange rate and equity markets using American Depositary Receipts (ADR) of each sampled country to synchronise time difference and structure of the sampled equity markets and also conditions on home country-specific factors. The study makes a unidirectional inference that exchange rates do affect equity market volatilities, evidence is further carried out by showing change in volatility of Chinese ADR pre-and post the 21 July 2015 unpegging of the Chinese Yuan from the USA dollar. The research uses a panel regression analysis and GARCH, to model data that is sampled from the period spanning 2001 and 2012 for 39 economies and samples variables such as population, consumption, unemployment, market capitalisation, closing price, stock volume, bid-ask spread and GDP per capita.

Jain and Biswal (2016) focus on the emerging economy of India to study the dynamic linkage amongst commodity prices, exchange rates and stock markets. The study uses daily data from 2006 to 2015 of the Bombay Sensex 30 as a stock market proxy, USA dollar–Indian Rupee exchange rate and spot commodity prices of crude oil and gold. The study applies a non-linear Granger non-causality approach and the dynamic conditional correlation (DCC) GARCH model to rationalise and study the time varying fluctuations in the sampled Indian markets. The study concludes that, for the case of India, which was the fourth largest oil consumer in the sampled period, both asymmetric and symmetric changes in oil and gold prices have influenced India's rupee and stock market. They suggest that gold in India, can be used as a store of value and in hedging inflation. Their study further argues that policy makers can further try to channel regulations through these commodities to manage domestic exchange rate fluctuations as there is an observed increase in their demand domestically.

Reboredo and Ugolini (2016) study the effects of oil price changes on stock market returns. Their research defines stock return quintiles and assess oil price shocks at low-, inter- and high-return quintiles for BRICS (Brazil, Russia, India, China and South Africa), United Kingdom (UK), United States of America (USA) and European Monetary Union (EMU) economies. The research finds that, prior to the 2008 financial crisis, oil price changes had limited impact towards equity markets and that extreme oil price shocks after the 2008 financial crisis intensified the influence, dependence and impact on equity market returns. They also highlight that, inter-quintile small and moderate oil price shocks did not have a significant influence in stock markets, while large downside spill-over effects were observed for the sampled economies. The study applies a Kolmogorov–Smirnov (KS) bootstrapping test to measure effects between their defined return-based quantiles, T-GARCH model and copula methodologies on weekly data spanning 15 years from Jan-2000 to Dec-2014.

Chkili (2016) uses an asymmetric dynamic conditional correlation (ADCC-GARCH) model on weekly gold and equity market data to study the time varying dynamic correlations that can be used in enhancing hedging effectiveness between the equity and gold markets for BRICS countries. The study concludes that there is a movement between positive and negative dynamic conditional correlations, tending to be negative during adverse economic financial periods and that if both asset classes are incorporated in an investment portfolio, they may improve risk-adjusted returns. While more researchers study only a mix of the emerging BRICS economies' reaction to oil price shocks, Raza et al. (2016) using a non-linear autoregressive distributed lag model (ARDL) model, shows that in addition to the large emerging economies within BRICS, other emerging economies are as well affected by oil and gold price changes and attribute this to change in the input costs that may add to or reduce profitability and hence market returns. Their study uses monthly data from onset stages of the financial crisis (Jan-2008 to Jun-2015) and looks at the impact of both gold and oil price volatilities on emerging economies.

Basher, Haug and Sadorsky (2016) researched the impact of oil price shocks on exchange rates by studying the origination of three oil price shocks for both oil importing and exporting economies. To capture and cater for nonlinearity at different regimes, they apply a two-stage Markov-Switching (MS) model to study the impact of oil price shocks. For their sampled oil exporting countries of Brazil, Canada, Norway, Russia and the United Kingdom (UK), they find that a positive oil shock causes an appreciation in those economies' domestic real exchange rates. The exception of Brazil is discovered when looking at the statistical insignificance brought by oil supply shocks relative to other sampled oil exporting countries. They find more complex non-uniform findings for oil importing economies but highlight South Korea as being negatively affected by both demand and supply oil price shocks.

Nguyen et al. (2016) use daily data from 1999 to 2010 to study the spill over between gold and stock markets for UK, USA, Indonesia, Japan, Malaysia, Philippines, Singapore and Thailand. The study makes a conclusion using a mix of copulas that, for some of the sampled economies, there is a relationship that shows gold as being a (safe) haven for some of the assets in the stock markets. This conclusion is however not consistent for all sampled economies as the researchers highlight that gold for the sampled period did not act as a haven for Indonesian, Japanese and Philippines stock markets.

Choudhry, Hassan and Shabi (2015) research stock market returns and their volatility and how they are affected by gold returns using non-linear causality tests conducted before and after the 2007/2008 financial crisis. The study samples return in the London Inter-bank Offered Rate (LIBOR) and gold, where quoted prices are in UK Pounds, US dollars and Japanese Yen. USA's Standard and Poor 500 (S&P 500), UK Financial Times Stock

Exchange 100 (FTSE 100) and Japan Nihon Keizai Shimbun 225 (Nikkei 225) are used as stock market proxies per economy and samples data between January 2000 and March 2014. The study finds that gold can only act as a haven during non-turbulent financially stable periods.

Gokmenoglu and Negar (2015) used the S&P 500 to study the interactions amongst the volatility of gold, oil and stock markets by applying the autoregressive distributed lag (ARLD) co-integration approach. The study found that the long run relationship amongst these variables exists but emphasise that gold prices have the highest impact on stock markets and are a good substitute to owning shares.

Fowowe (2015) studied the causality relationship between equity and currency for the South African and Nigerian markets. The study uses monthly data from January 2003 to December 2013. The research makes findings using a VAR model, amongst them that for Nigeria, there is a unidirectional relationship between the naira (domestic currency) and the Nigerian Stock Exchange (N.S.E), proving the flow-oriented model. The research also highlights the external influence from the London Stock Exchange that is significantly exerted on both economies which were the two largest economies (by GDP) in Africa during the sampled period.

Ahmed (2014) studies the relationship between the stock and exchange rates markets of Egypt during and before the 2011 political uprisings. The study splits daily data from 9 November 2008 to 31 October 2013 into two regimes using 25 January 2011 as a cut-off date. The study uses an error correction E-GARCH model to make inferences on mean and volatility movements between the markets. The research finds that during the uprising there was a unidirectional transmission from the stock market to the foreign exchange market.

The level of oil dependence may be expected to be an amplifying and influential factor to economic impacts stemming from an oil price shock. Grigoli et al. (2014) show that oil dependence by an economy is not influential during an oil price shock, they highlight the importance of currency policy and regime instead as being a buffer factor during an oil price shock. The conclusions are made by using a linear regression framework, that classifies policy and none-policy explanatory variables to model data from the 2014 to 2016 oil price plunge and assess the impact on 44 economies. The study makes conclusions based on several explanatory variables including oil dependence, (economic) diversification, macroeconomic policy and structural flexibility.

Commodities such as oil and gold, have anticipated economic impacts that are dependent on it being either an input or output in an industry or economy. Degiannakis, Filis and Floros (2013) use varying industrial sector level indices to check the effect oil price shocks have on sector-specific stock market returns. They use ten European sectors and their data is applied on a diagonal-VECH GARCH model to assess time varying correlation and conclude that there is an industry level effect on returns that emanates from oil price changes.

Wang, Wu and Yang (2013) used monthly data from a mix of oil exporting and importing economies to see the effect oil price shocks have on the economies' stock market. They use a structural vector autoregressive (SVAR) model to study the effects of oil shocks emanating from the mismatch in crude oil's demand and supply. They conclude that crude oil supply is an exogenous factor due to OPEC's unpredictable and somewhat politically induced events and activities. Their conclusion also highlights how varying sources of oil price shocks are crucial and can have differing effects depending on whether an economy exports or imports crude oil.

Ciner, Gurdgiev and Lucey (2013) use bonds, stocks and currency returns data from USA and UK, gold and oil markets. Their study uses a DCC–GARCH to model daily data from January 1990 to June 2010. They define quintile regressions to check for time variation in the conditional correlation and dependence between these asset classes during extreme market scenarios. Using conditional correlations, they also research whether any of these assets can act as safe zones or havens towards each other when included in a portfolio. They find that, for both markets (USA and UK), gold acted as a safe haven as it was able to show distinguishable conditional correlations patterns, between itself and the rest of the sampled variables.

Aloui, Khuong and Njeh (2012) profile emerging countries on the basis of their oil trade and dependence by defining crude oil trade based categories of largest net-oil importing, moderately oil-dependent and large net-oil exporting economies. They used these categories for twenty-five emerging economies to study the impact oil price fluctuations have on equity market returns. They use daily closing index prices' data spanning for 10 years from 29 September 1997 to 2 November 2000. They apply a multifactor regression model to data from each of the sampled country's oil, stock market and exchange rate returns and find that stock returns are risk sensitive depending on the economy's crude oil dependence. Arouri, Jouini and Nguyen (2012) study oil price fluctuations on various economic sector level European stock markets using a VAR-GARCH model, due to its ability to capture volatility, on weekly data from 1 January 1998 to 31 December 2009. Their study researches hedge-ratios to find optimal stock optimisation levels to encounter the effect oil price shocks. They conclude that various sectors, depending on their level of dependence to crude oil are affected directly or indirectly by oil price changes.

Nguyen and Bhatti (2012) using the economies of China and Vietnam applied copula and other non-parametric methods including chi-plot and Kendall's K-plot to test the relationship and dependence between oil and stock markets. They show evidence of tail-dependence for Vietnam's economy for the sampled asset classes. The research uses 11 years of daily data from 1999 to 2010. Masih, Peters and De Mello (2011) study the economy of South Korea's reaction to oil price shocks using a vector error correcting (VEC) model to check for impact on the domestic stock market on monthly data from 1 May 1998 to 31 January 2005. Their study found that real stock market returns were the main channel, in the short run, at which oil price shock had a long run effect on the economy's stock market for the case of South Korea based on the effect oil price shocks have on firms' operational costs and hence long run anticipated profit margins. Sujit and Kumar (2011) used daily time series data of gold price, exchange rate, S&P 500 index and oil price from Jan-1998 to Jun-2011 and apply a Vector Autoregressive (VAR) approach to study how gold prices were affected by changes in oil prices, exchange rates and equity markets. Their study concludes that both gold and oil have behaved as risk deterrents through their inverse price linkage with stock and exchange rate markets. They also mention that the prices of oil and gold are dependent amongst each other and on various complex qualitative factors such as government policies and budget and their study link the rise of Canada (an oil and gold exporting economy) to the rise of prices over the years.

Using data from the initial stages of the 2008 financial crisis for net oil exporters and importers, Filis, Degiannakis and Floros (2011) find no significance in distinguishing sampled economies on oil-exporting status. The research uses an asymmetric Dynamic Conditional Correlation GARCH framework with Glosten, Jaganathan and Runkle factor (DCC- GJR-GARCH) on data spanning between 1987 and 2009 from various economies including oil net-exporters; Canada, Mexico and Brazil, and oil net-importers; USA, Germany and Netherlands. The study acknowledges that, there is an influence from oil price shocks to stock markets, but it is irrelevant to categorise economies on exporting or importing conditions because the sampled economies were all observed to have a similar behaviour or reactions. The study also highlights that demand-side shocks have a unique behaviour that relates oil and stock markets, but supply-side shocks are not that influential to the relationship.

Miller and Ratti (2009) study the relationship between crude oil and stock markets of USA, UK, Canada, France Italy and Germany. The study uses a vector error correction model (VECM) on monthly data between 1971 to 2008 and it finds evidence of periodic none-consistent negative relationship between real oil prices and stock markets. The research highlights that between certain selected time-breakage points, regimes or time series segments, the relationship of the studied variables do not show consistent statistical significance such that it ceased to exist towards the end of 1999, proving the evolution in time on how oil impacts stock market activity and also showing how stock markets were becoming more diversified.

Lescaroux and Mignon (2008) offer additional insights to the impact of oil shocks to economic activity by studying the impact of oil towards a number of economic variables including GDP, consumer price index (CPI), house-hold consumption, unemployment and stock prices. Their study categorises 36 economies on oil export and import status, dividing OPEC constituents, major exporters and importers. The study uses annual data from 1960 to 2005, to construct cyclical correlations and applies Granger causality tests amongst sampled economic variables and crude oil. The study finds non-uniform influence amongst oil and the sampled variables, but where it exists, it is found to be mostly moving from oil towards the economic variables, with strong emphasis being made on bidirectional stock market and oil relationship for oil exporters. Also, the relationship between oil and CPI (as a measure of inflation and interest rates) is also examined and mentioned as being critical to oil being influential to economic activity.

Blanchard and Gali (2007) study the role of oil price shocks on oil consumers, oil producers, households and firms in the economies of United States of America, France, Germany, United Kingdom, Italy and Japan. The study uses as variables, oil prices, GDP, employment, CPI and wages. The research uses data from January 1970 to April 2005 and a Structural Vector Autoregressive (SVAR) model. The study applies several theories to show the role of crude oil on several economic variables. A Cobb Douglas production function is used to link domestic output, labour and the amount of imported oil used in producing domestic output. The study also links total consumption to domestic output and consumption of imported oil. Domestic output and consumption are priced such that their difference is made of a portion of real price of oil, such that an increase in real price of oil will increase consumption relative to domestic output. The study finds that, a smaller share of oil in production, flexible labour market and improved monetary policies have been influential in the dampening of oil in affecting economic activity over the years. Hooker (2002) argues that commodity price shocks in general are partially passed through in the form of core inflation. The study uses quarterly data sampled from February 1962 to January 2000 and models the data on a Philips curve regression framework to study the contribution of oil price changes to economic activity specifically inflation and unemployment. The study finds, using various measures of inflation, that oil was influential to core inflation before 1981 but little evidence has been observed of the pass-through effect from oil post 1981.

There are researchers that have highlighted the existence of alternative channels between commodities and influential economic variables that are outside of the direct financial sector and where commodities are not a direct input or output. This phenomenon is due to factors such as remittances, foreign direct investments and aid, being influential to capital flows. Akçay and Karasoy (2019) for instance, show how remittance is affected by commodities such as oil and how this impact has had a direct role to the economic growth in Egypt. The study uses annual data from 1980 to 2005 and is based on a linear combination of variables such GDP of Egypt, economic growth rate (of migration country), level of domestic credit to private sector (as a percentage of GDP), foreign exchange rate, oil price, economic instability (made up of a linear combination of inflation and external debt) and the average GDP of OECD economies. The study highlights how remittance as a percentage of GDP has grown due to growth in migration and is influenced by factors including political instability, exchange rates, prices of oil in Egypt post the 2011 uprisings. Harb Sayed Ahmed (2019) also add that the growth of the tourism sector in Egypt has had influence in and is a source of foreign exchange. The study uses monthly data from June 2010 to December 2019 and applies an ARCH GARCH model to make inferences. The study finds a unidirectional relationship that is positive and from exchange rates to the stock prices of tourism focused firms. Addison et al. (2017) focus on the impact aid and policy have on the real exchange rate of Morocco and Tunisia by controlling for remittance and foreign direct investments. The study makes a finding that aid did lead to the appreciation of real exchange rate for Morocco’s dirham but not for Tunisia’s dinar. The study uses a VAR model and data from 1980 to 2009, to exclude the Arab uprising periods from the study. Included as variables in the study are remittances (as a percentage of GDP), aid (as a percentage of GDP), foreign direct investments (as a percentage of GDP), growth of manufacturing sector, government consumption (as a percentage of GDP), terms of trade and monetary supply.

A study by Cyrille (2015) also shows how international reserve accumulation by CEMAC member economies has played an important role in linking trade markets and influencing exchange rates. The study uses quarterly data from January 1985 to April 2009 to show how uncertainty, change in economic growth and minimum adequacy requirements by the regional central bank BEAC, have led to the increase in demand for international reserves for the six member economies of CEMAC. The study by Hegerty (2013) also highlights another channel, exchange market pressure (EMP), as being critical to dynamically linking commodity, exchange rates and stock markets. In the study EMP is defined as a currency crisis in an economy and can be triggered by capital flows. The study uses monthly data from December 2001 to August 2012 and samples regionally adjacent economies of Gambia, Ghana, Nigeria and Sierra Leon. Included as part of the study is a commodity index that consists of oil, gold, cocoa, copper; and stock market data of the USA, France, South Africa and WAEMU (West African Economic and Monetary Union) and these are added to study the impact from external economies to the region. The study uses a VAR model to study the linkages of shocks amongst the sampled markets. The study finds that there are EMP spill-overs between markets, for example the unidirectional flow of Gambia' EMP to Nigeria EMP, but highlighted is the overall dominant impact of regional economies relative to outside economies.

2.4 The Role and Inclusion of African Economies in Commodities Markets

Globally, most emerging economies have benefited immensely from aligning their commodity trading policies to achieving growth, an approach which broader African countries can or are also adopting. An episodic evidence is the immense growth experienced by emerging economies in 2016, when China and India experienced GDP growth levels of 6.7% and 7.5%, respectively. China and India have also experienced, respectively, a 203% and 129% increase in oil consumption, respectively between years 2000 and 2016 (Hameder, 2017). In 2016, China and India imported nearly 595 million tonnes of crude oil globally, of which 100.4 million tonnes (17% of their import for the year 2016) were from Africa. African states only imported 26.3 million tonnes in 2016, of which 10.8 million tonnes (41%) were intra-African imports. In 2016, Western and Northern African countries exported 6.1 million barrels per day nearly 10% of the 65 million barrels exported per day globally. African oil producers in 2016 had produced 11% of the crude oil produced globally. Between the years 2000 and 2016, the African continent consistently produced between 10% and 14% of the global oil (BP Statistical Review of World Energy 2017). Though this study samples gold and oil as commodities, but the crude oil production-consumption difference stated above warrants a generic objective quantitative answer to a question of whether oil or any other commodity being exported or imported, has influenced over or is influenced by stock and exchange rates market in the African continent.

Using the African Development Bank's (AFDB) data, most African countries have either gold and crude oil either as a primary or secondary exported commodity. If there is a dynamic relationship, dependence or impact between markets of oil, gold, exchange rates and equities; such a phenomenon should be visible in their time varying dependence and correlation structure. As most sampled economies are open-and trade with global economic participants, there is an anticipated distinction in the way the sampled variables relate for exporters and importers. The oil price stabilising reactions from OPEC constituents and non-OPEC oil producers should be anticipated to show a varying impact on the sampled African stock markets and exchange rates through oil and gold price shocks as it has previously been observed for larger developed economies (Basher and Sadorsky, 2006; Basher, Haug and Sadorsky, 2016; Reboredo and Ugolini, 2016). The impact of commodity price shock is also expected differ for a commodity exporting and importing economies.

The African continent is developing, market-liberalizing, modernising and growing; hence the demand for energy inputs, oil specifically, is anticipated to grow in line with these future developments (Arouri et al., 2014). Oil price innovations have been noted to negatively impact emerging economies in general (Raza et al., 2016). In contrast to developing and emerging economies, technological advancement has allowed developed economies to rationalise usage and diversify sources of energy as they move towards renewable energy and less capital-intensive approaches to extracting minerals. Anticipated growth in demand for energy for African states has a limited scope of being counterbalanced or compensated for by growth in energy supply, though alternative and diversified energy sources are being used globally. African markets in general are becoming more open, flexible and sophisticated and will meet global standards in terms of trading volume, technology, market making and infrastructure; these developments will be conducive to economic growth (Enisan and Olufisayo, 2009). With the anticipated increase in reliance on energy exports and imports from developed economies there is a need to view the effect that major assets gold and oil have on the states' stock and exchange rate markets. Also, with the proof of the stock (and flow) oriented model showing transmission and impact moving from stock markets to exchange rates (and vice versa), this work aims to find, if there exist a dynamic dependence of the sampled commodities, the equity and exchange rates markets on the predominant African economies. The main aim of this study is to examine the causal-relationship, dependence and co-movements amongst gold, crude oil (exports and imports).

The impact of energy consumption and primary commodity price movements on economic growth has propelled most of the research that has been conducted on economies in the African continent. The broader research has concentrated on change in energy demand emanating from the growing population and primary raw commodities that most African economies export at volatile prices. Extensive research has been conducted for developed economies but there is still a lack of research that looks specifically at African economies, though these economies export several primary commodities that are inputs in the manufacturing of various products globally. There is still a limited number of research-papers that incorporate countries that are not large relatively to developed economies. Sampling relatively small economies will give insights on how some of the existing literature's conclusions might hold given the size and pertinent economic activity drivers of an economy. Though some African economies have been included in research papers as some are globally significant commodity exporters and some are part of organisations such as the OPEC cartel, economies where commodities are non-primary exported goods (or the economy is not part of a global economic union) have not been widely included or researched.

Though oil has been a focal research topic globally, the adding of gold to the analysis gives weight to the ability of this research to make additional concluding remarks regarding commodities generally traded in the African continent. Gold as a commodity has not been well included when looking at commodities that are influential in the African continent but is prevalent as either a primary or secondary imported or exported good in the continent. The interaction of both gold and oil in a model will be tested to examine their influence on the sampled economies. Also, knowing the direction of possible causality and level of dependence amongst the sampled variables would be beneficial to policy makers in the less relatively sampled economies. The extending of the sampled period would allow the inclusion of the 2008 global financial crisis and the effects that may have emanated from its unfolding and disallow for sampled period biasness.

2.5 Chapter Summary

The empirical research shows that commodity prices do have an ambiguous relationship to economic variables such as exchange rates and stock markets, but this relationship is sensitive to multiple factors such as sampled period and country-specific dynamics affecting an economy. The commodities and economic variables relationship are also argued to be conditional on the availability and usage of the commodity on a macro and micro level per economy. Deaton (1999), Basher and Sadorsky (2006) and De Gooijer and Sivarajasingham (2008) mention that a lot of the research done around the topic of commodities and economic activity is based on viewing, and has had findings regarding, the influence developed economies exert on lesser developed countries. From the observed literature it becomes vivid that there is a notable lack of African economies mentioned or represented in the research thus far except for those that are constituents of BRICS or OPEC. There is also a lack of research that distinguishes how the economic variables are related to commodities when the commodities are imported or exported by an economy. There is also a notable variation in the results from developed and large emerging economies when looking at their economic variables' relationship with commodities' price shocks. Developing economies have been highlighted to have a contradicting and non-consistent relationship when sampled by researchers, such as how some cases have highlighted varying conclusions for developing economies like Brazil and South Korea to those of developed economies. Deaton (1999) and Rogoff and Chen (2003) argue that the inconsistency is derived from most emerging economies trading in the commodities markets as price takers while having a slight market share and influence.

This dissertation will contribute towards understanding whether the broader conclusions made for developed or large emerging economies hold for relatively smaller and specifically African countries as they are less sampled in empirical studies. The inclusion of African economies will allow policy makers and the broader investor community to have insights to possible consequential changes that may occur due to the dependence and correlation structure depicting the relationship of the sampled variables. The ensuing section gives an overview of the methodology that will be applied in the analysis.

3 Methodology

3.1 Introduction

This chapter introduces the chosen analytical model and its applied framework. The model with its limitations and diagnostics will be discussed and from section 4.2 applied to empirical data. This chapter gives a view of the required conformations and underlying assumptions. In sub-section 4.3.7 the models post application will be checked for robustness and consistency. To provide responses to the research questions in section 1.5, this dissertation adopts, and this chapter provides a discussion on the vector autoregression copula-based multivariate generalised autoregressive conditional heteroskedastic (VAR CMGARCH) approach to study the relationship that may exist amongst the considered financial and economic variables and the two sampled commodities.

The generalised ARCH model, initially proposed by Bollerslev (1986), is chosen for its ability to capture both the conditional and non-conditional variance, flexible lag structure and by allowing variance to be a function of its past shocks. From the model's conditional variance structure, conditional correlations are derived and that allows for a level of clarity on the time varying dependence. The sampled variables have been discussed in chapter 1 on how they relate to economic performance and this dissertation seeks to potentially show their dynamic relation to one another. Hence, if the variables are related with known dependence and covariance structure, there could be a level of ease at which economic performance can be ideally altered from circumventing an eventual or follow-up adverse shock from knowing and observing co-movements and trends of the variables. The GARCH model also allows, in its multivariate form, viewing of the correlation and dependence structure (through a copula) of the sampled variables through time. From the volatility model one can also show if the relationship between the variables is dynamic, constant or directional. The underlying assumptions of the GARCH models extend mainly from autoregressive heteroscedastic conditional (ARCH) model by Engle (1982). Various forms of ARCH models exist with each version derived specifically to capture some observed properties of financial data such as non-linearity, non-normality, cointegration, leverage and asymmetry. Glosten, Jagannathan and Runkle (1993) show the misspecifications found in the GARCH in the mean (GARCH–M) and exponential GARCH–M (EGARCH-M) models and introduced a threshold GARCH model that captures the different impact from positive and negative returns to conditional variance, an idea that is also extended by Zakoian (1994).

In the multivariate case, where a basket of k – number of assets (k = 4) are involved, assessing each asset's conditional variance and covariance's movement over time in relation to or given the other remaining assets, allows for a viewing of an indication of potential conditional risk towards returns. There are a number of multivariate volatility or GARCH models developed by researchers over the years such as; the constant conditional correlation (CCC) by Bollerslev (1990), Baba, Engle, Kraft and Kroner (BEKK) by Engle and Kroner (1995), the dynamic conditional correlation (DCC) by Engle (2002) and the time varying correlation (TVC) by Tsui and Tse (2002). Each model has prolonged the idea of the original standard or vanilla GARCH model and offered varying conditional multivariate volatility assumptions and approaches. Engle (2002) and Tsui and Tse (2002) proposed the DCC and TVC GARCH models, respectively. The models have the ability to capture time varying linear correlation that are able to show linear degree of dependence among variables through time. Empirical research surveyed in the literature review section of this dissertation has argued and pointed out how financial data has varying dynamic non-normal dependence that is conditional on economic periods of market turbulence and calmness, which cannot be captured by linear correlation measures. Testing properties such as skewness and kurtosis in financial data shows how it can be limiting to assume non-deviation in symmetry and normality when scrapping for insights or forecasting. Sklar (1959)"coins" the term "copula" and uses pre-existing methodologies to define a theorem that couples a joint distribution to its marginals (and a copula for independence measure) and uses it to show how better enabled, than linear correlation, unconditional copulas are better at capturing the dependence structure of a number of variables regardless of family. Patton (2006) stretched the idea of unconditional copulas into a time varying ideation that can be applied in studying dependence using conditional copulas. Lee and Long (2009) are some of the authors that synthesise the unconditional copulas and MGARCH ideas in a multivariate case by arguing for copula based multivariate GARCH (C-MGARCH) models that are able to separately model linear correlation and dependence through a copula.

The copula based variance models can depict the dynamic relationships amongst the variables and in a way respond to some the research questions of section 1.5, but additionally, inferences have to be made regarding information flow of the sampled variables' returns and volatility. The information flow amongst variables can give insights on their conditional causality relation and further argue lead, lag and feedback connectedness. For two joint distributions or stochastic processes $\boldsymbol{X_t}$ and $\boldsymbol{Y_t}$, if the past values of $\boldsymbol{X_t}$ enable better determination, prediction or explanation of $\boldsymbol{Y_t}$ (or its future values) beyond using its own past information, then $\boldsymbol{X_t}$ is said to Granger-cause $\boldsymbol{Y_t}$ (Granger, 1969). Granger causality (G-causality or G-C) in the latter mentioned example of stochastic processes $\boldsymbol{X_t}$ and $\boldsymbol{Y_t}$, can results in spurious G-C modelling of the variables if there exist another statistically significant and G-causal variable, $\boldsymbol{Z_t}$, that is omitted from consideration when analysing $\boldsymbol{X_t}$ and $\boldsymbol{Y_t}$. Amongst other researchers, Geweke (1984) proposes conditioning on the common effect of the additional variable $\boldsymbol{Z_t}$ to condition out its impact from $\boldsymbol{X_t}$ and $\boldsymbol{Y_t}$ and determine conditional G-causality between processes. G-causality modelling will be applied in this dissertation to analyse potential causality in the mean or returns' model as causality in variance will be assessed using non-causality test by Hafner and Herwartz (2006). The subsections below introduce conditional models that are required and will be used in this dissertation to resolve the research questions.

3.2 Autoregressive and GARCH Models

The univariate autoregressive (AR) model shown in equation (1) is the epitome of this dissertation and relates an asset return at time t with previous returns at time s ($0 < s \leq t - 1$, $s \in \mathbb{R}$). [1] The AR model can be extended into a generalised vector AR (p) model and both the univariate and multivariate form are assumed to have error terms with conditional variance that is persistent and are used to study the dynamic relation and dependence of the variables. The univariate autoregressive AR (1) model can be mathematically expressed as follows:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t , \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{1}$$

r_t is considered as the return of an asset at time t and is expressed as difference between consecutive periods in logarithmic form. β_1 represents the effect of past shock, r_{t-1}, to the return at time t, r_t. $\boldsymbol{\beta_0}$ is the intercept and a constant and has various interpretations in econometrics, such as representing the autonomous or mean level of a series. If there exist a unit root, i.e. if $\beta_1 = 1$ in the equation, then equation is said to be a nonstationary random walk process (that can have a drift). The unit root (when $\beta_1 = 1$) may have and cause persistent correlations that continue as the sample increases resulting in a spurious model. Generally, a condition is added, i.e. is $|\beta_1| < 1$ for the above equation to be stationary. Unit root testing is done with the aim of checking for the existence of unit roots in the variables by regressing the dependent variable on its lag variable(s) and checking for the existence of a unit coefficient. The inference on the existence of a unit root is made after performing unit root test(s) with the null and alternative hypothesis dully expressed as follows:

$$H_{null}: \beta_i = 1 , \qquad H_{alt.}: |\beta_i| < 1$$

This dissertation adopts the augmented Dickey Fuller (ADF), Kwiatkowski–Phillips–Schmidt–Shin (KPSS) and Zivot-Andrews (ZA) tests to test for the existence of unit roots and infer stationarity even in the presence of an unknown structural break in the marginals.

[1] There are alternative ways for expressing the relation including those, not mentioned specifically in this section, applied when using an asset's moving averages (MA).

The ADF-test applies the t-ratio of least squared estimate of the beta coefficients, β_i $i \in \mathbb{R}$, and for the univariate case can be expressed as follows:

$$ADF_{Test} = \frac{\hat{\beta}_1 - 1}{Standard\ Error(\hat{\beta}_1)} \tag{2}$$

$$KPSS_{Test} = \sum_{t=1}^{T} \frac{S_t^2}{\sigma_{\varepsilon}^2} \tag{3}$$

In equation (3), $S_t = \sum_{i=1}^{t} e_i$,where e_i's represent the residuals and $\boldsymbol{\sigma_{\varepsilon}^2}$, an estimate of error variance from summing the squared residuals and dividing by the length, T, of the timeseries (Kwiatkowski et al., 1992). The ZA test by Zivot and Andrews (1992)is applied to assess the possible existence of a unit root when there is a structural break in both the trend and intercept or rate of growth at an unknown point in the series. The ZA test uses results of the lowest t-value from the Dickey-Fuller test and uses that as a breaking point from which to test the existence unit roots. The truncation lag value used for the ADF test is based on Phillips and Perron (1989) methodology that can be expressed as follows:

$$\text{Lags}_{max} = \quad 12\left(\frac{T}{100}\right)^{\frac{1}{4}} \tag{4}$$

where T in the equation (4) represents the length of the series.

The existence of serial autocorrelation or correlation in residuals over time with their lagged values is tested to find if there is serial dependence of the deviation errors found in the model. The testing of the relationship amongst errors of the model will enable confidence in knowing the structure and potential impact of previous error terms $\boldsymbol{\varepsilon_{t-i}}$, i > 0, to the error at time t, $\boldsymbol{\varepsilon_t}$. Once the test is performed, a proper model can be used to capture the autocorrelation and the order of serial correlation and prevent misspecification, bias estimates and improve inferences from the model. For this dissertation, the Ljung-Box test is performed on the residuals from the model. The test examines m, $m \in \mathbb{R}$, autocorrelations of the residuals to detect the adequacy of the fitted model. Given error terms or residuals $\boldsymbol{\varepsilon_1}, \dots, \boldsymbol{\varepsilon_n}$, the Ljung - Box test can be mathematically expressed as:

$$\tilde{Q}(m) = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k} \tag{5}$$

where:

$\widetilde{\boldsymbol{Q}}(\boldsymbol{m})$ is a chi-square random variable with m degrees of freedom, $\boldsymbol{\chi^2_m}$

$$\hat{\rho}_k = \frac{\sum_{i=k+1}^{n} \varepsilon_i \varepsilon_{i-k}}{\sum_{i=1}^{n} \varepsilon_{i=1}^2} \tag{6}$$

The test uses the following null hypothesis:

$$H_{null}: \hat{\rho}_1 = \hat{\rho}_2 = \cdots = \hat{\rho}_m = 0$$

Against the alternative:

$$H_{alt}: \hat{\rho}_i \neq 0 \; for \; some \; i \in \{1, \dots, m\}$$

The resulting decision is based on a predefined significance level (α) against a calculated probability value, and the null hypothesis is rejected if probability or p-value is less than or equal to the selected significance level or if $\widetilde{\boldsymbol{Q}}(\boldsymbol{m}) > \boldsymbol{\chi^2_\alpha}$. This test will be performed for each series of the sampled variable. The sampled autocorrelations, $\hat{\rho}_i$ for $i \in \{1, 2, \dots\}$ will be used to estimate autocorrelations ρ_i for $i \in \{1, 2, \dots\}$ to perform the test. The Ljung–Box test however is known to be inconsistent as increasing the number of lags does not translate to the increase in the probability of rejecting the null hypothesis of no serial dependence. Hence, the number of lags chosen is critical to the test as they influence the results and performance of the test and this dissertation applies a methodology suggested by Tsay (2010) which is expressed in equation (7).

$$\text{Lags}_{Ljung-Box} = ln(T), \tag{7}$$

where T in the equation (7) represents the length of the series

Post fitting an autoregressive model, certain behaviour is tested in the residuals to ensure model adequacy. Residual properties or behaviour such as normality, arch effect and serial dependence are tested from the fitted model to infer the existence of any relationship amongst them. Various tests exist to check for normality, for this dissertation the skewness, kurtosis properties as reported in the Jarque-Bera (JB) of Bera and Jarque (1981) and Shapiro-Wilks (SW) of Shapiro and Wilk (1965), will be used. The Jarque-Bera and Shapiro-Wilks tests use as a null hypothesis that the data being tested can be considered as generated by a normally distributed function. The JB and SW normality tests can be mathematically expressed as follows:

$$JB = \frac{T}{6}\left(\hat{S}^2 + \frac{\left(\hat{K}-3\right)^2}{4}\right) \tag{8}$$

where the sample skewness (S) and kurtosis (K) can be respectively expressed as:

$$\hat{S} = \frac{1}{(T-1)} \frac{\sum_{i=1}^{T}(r_i - \hat{\mu}_r)^3}{\hat{\sigma}_r^3} \tag{9}$$

$$\hat{K} = \frac{1}{(T-1)} \frac{\sum_{i=1}^{T}(r_i - \hat{\mu}_r)^4}{\hat{\sigma}_r^4} \tag{10}$$

In equations (8), (9) and (10), T is the size or duration of sample being tested, $\hat{\mu}_r$ is the sample mean and $\hat{\sigma}_r^2$ is the sample variance. When the data is assumed to be normally distributed the sample skewness (S) is also normally distributed with a zero mean and variance of $\frac{6}{T}$ whereas the sample kurtosis (K) is also normally distributed with a zero mean and variance of $\frac{24}{T}$ (Tsay, 2010). Shapiro, Wilk and Chen (1968) show the power of the SW test in detecting normality in a dataset and mention that for most normality tests, the results are sensitive to the sample size. The Shapiro-Wilk normality test can be mathematically expressed as follows:

$$\widehat{SW} = \frac{\left(\sum_{i}^{T} a_i \, \hat{r}_{(i)}\right)^2}{\sum_{i=1}^{T}(r_i - \hat{\mu}_r)^2} \tag{11}$$

In equation (11), $\hat{r}_{(i)}$ represents ordered returns where $\hat{r}_{(i)}$ is the i^{th} order statistic in a sample of returns; and a_i represent linear unbiased coefficients found from a linear representation of r_i assuming an unknown mean and variance . At an α level of significance the tests use as critical values, the chi-square distribution with two degrees of freedom (Shapiro and Wilk, 1965).

Conditional heteroscedasticity or ARCH effects are tested in the model to understand the time evolution and behaviour of the conditional variance at time t in relation to past or lagged variance and to model variance clustering. Understanding heteroscedasticity and structure of the conditional variance enables modelling of the impact of lagged variance to current variance hence enhancing model inferences and forecasting ability. The above mentioned Ljung–Box test is performed on the squared residual series and as mentioned above uses a significant critical value to make inferences on the existence or non- existence of ARCH effects. From the inference, a proper ARCH or GARCH model can then be applied to properly model the variance.

A univariate AR (p) model (an extension of the AR (1)) is mathematically expressed in the equation below and conditions expressed above for the AR (1) are still applicable:

$$r_t = \beta_0 + \sum_{a=1}^{p} \beta_a r_{t-a} + \varepsilon_t \, , \qquad \varepsilon_t \sim N(0, \sigma_t^2) \tag{12}$$

The conditional variance expressed above, σ_t^2, can be represented in various forms but for this dissertation it is expressed similarly to Glosten, Jagannathan and Runkle (1993) and Nelson (1991) to capture asymmetric properties of financial data. The two models, GJR-GARCH and EGARCH are respectively expressed in the ensuing equations below.

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{x} (\propto_i + \gamma_i N_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{y} \delta_j \sigma_{t-j}^2 \qquad (13)$$

where:

- $\boldsymbol{N_{t-i}}$ is an indicator and dummy variable that is used to represent or detect asymmetric and leverage effects of financial data, such that if $\boldsymbol{\gamma_i} \neq \mathbf{0}$ then there exist either inverse- asymmetric or asymmetric effect:

$$N_{t-i} = \begin{cases} 1 & if\ \varepsilon_{t-1} < 0 \\ 0 & otherwise \end{cases}$$

$$ln(\sigma_t^2) = \omega_0 + \sum_{i=1}^{x} \propto_i \frac{|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{y} \delta_j\ ln(\sigma_{t-j}^2) \qquad (14)$$

where:

- γ_i and $\propto_i$ capture the size and sign effects respectively and represent or detect asymmetric and leverage effects of financial data.

In equations (13) and (14), $\boldsymbol{\propto_i}$ (or ARCH term) indicates the short run effect that past innovations have on the variance at time t .The GARCH term, δ_j, represents the long run impact past variance values have on the present variance at time t. The ARCH and GARCH term both represent the persistence ($\hat{P}$) of the conditional variance. For the GJR-GARCH, three terms, $\propto_i,\ \delta_i\ and\ \gamma_i$, when combined represent the overall persistence of conditional variance, whereas this is achieved using the sum of only the $\delta_i$term for the EGARCH. Respectively for a vanilla, GJR and exponential GARCH a formal definition of persistence is given below, where k represents the expected number of non-positive standardized residuals:

$$\hat{P}_{Vanilla} = \sum_{i=1}^{x} \propto_i + \sum_{j=1}^{y} \delta_j \tag{15}$$

$$\hat{P}_{GJR} = \sum_{i=1}^{x} (\propto_i + \gamma_i\, k) + \sum_{j=1}^{y} \delta_j \tag{16}$$

$$\hat{P}_{Exp} = \sum_{j=1}^{y} \delta_j \tag{17}$$

The following conditions and assumptions are made for the vanilla and GJR GARCH models to be stationary, whereas, due to the logarithmic expression of the EGARCH model there are no required restrictions to ensure positiveness of conditional variance.

$$\omega_0 > 0, \propto_i \geq 0\,, \delta_j \geq 0 \;\; and \;\; \sum_{i=1}^{max(x,y)} (\propto_i + \delta_i + \frac{1}{2}\gamma_i) \approx 1\,, for\ i,j$$

The models extend to a univariate ARMA (p_1, q_1) – GARCH (p_2, p_2) model, $q_1 = 0$ as there are no MA or moving average terms expressed. In univariate models there are cases where the persistence of the conditional variance is slightly above one (Bauwens, Hafner and Laurent, 2012).

A multivariate case of the autoregressive, VAR (p) model, extends from the univariate AR (p). Below is a mathematical expression of a model representing a vector autoregressive of order one[2] VAR (1):

$$\boldsymbol{r_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 r_{t-1}} + \boldsymbol{\varepsilon_t} \tag{18}$$

where:

$$\boldsymbol{r_t}^{\boldsymbol{T}} = (Gold\ Price_t\,, Oil\ Price_t\,, LCU\ in\ USD_t\,, Stock\ Market\ Index_t\,)$$

[2] NB Bold letters represent matrices

and

$$\boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, \boldsymbol{H_t})$$

Using the vector / matrix representation $\boldsymbol{r_t}$, $\boldsymbol{\beta_0}$ and $\boldsymbol{\varepsilon_t}$ are m-dimension vectors representing returns, intercept or average and error terms, respectively. $\boldsymbol{\beta_1}$ is an m -by- m matrix with each element representing the effect of the first lag return to each corresponding time t return element of $\boldsymbol{r_t}$. The error term vector, $\boldsymbol{\varepsilon_t}$, is an m -by-1 white noise innovations with mean zero and covariance matrix $\boldsymbol{H_t}$ (Tsay, 2010).

The vector autoregressive model of order p, VAR (p), extends the VAR (1) and can be mathematically expressed as follows:

$$\boldsymbol{r_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 r_{t-1}} + \boldsymbol{\beta_2 r_{t-2}} + \cdots + \boldsymbol{\beta_p r_{t-p}} + \boldsymbol{\varepsilon_t} \quad (19)$$

where: $$\boldsymbol{\varepsilon_t} = \boldsymbol{H_t^{1/2} Z_t}$$

In equation (19), each of the dependent variables will also form part of the independent variables for each of the variables to enable a dynamic relationship insight generation. A linear combination of two or more stationary variables is regarded as co-integrated if they share a common stochastic trend, hence an additional test (Johansen Test) is applied to check for the requirement to fit a Vector Error Correction Model instead of VAR.

Parameters of the return vectors can be estimated using a maximum likelihood estimation (MLE) and not ordinary least squares (OLS) methods. This is because the OLS estimation process is generally used to estimate the parameters of a liner relationship between dependent and independent variables but includes as its main assumption homoscedasticity or constant variance and no linear relationship amongst variables. To show dynamic relationship amongst the sampled variables and conditional variance would be in violation of the OLS method. Hence, the maximum likelihood estimation (MLE) process is used to find the estimates of the return vector variables. The MLE estimates parameters that maximise the log-likelihood or probability measure and has the advantage of adapting to independently, identically distributed error terms. For variables in the return vector there are instances, such as the none-existence of a financial equities market in a sampled economy, where data availability may limit the estimation and number of variables to be estimated.

To test or specify the order of the VAR (p), the number lags to be included in the model, this dissertation will use a mix of information criteria (e.g. AIC and BIC). For each of the sampled economies the price of gold and crude oil will not be reflected in the country's local currency unit (LCU) relative to the US dollar (USD) because the LCU is also endogenous to the model. The AIC (and BIC) used in the model selection, are formally defined in equations (20) and (21) below using k as the number of parameters in the model being assessed, T as the length of the series and L as the model's value of the maximum likelihood function.

$$AIC = \frac{-2}{T} ln(L) + \frac{2}{T} k \tag{20}$$

$$BIC = \frac{-2}{T} ln\, L + k\, ln(T) \tag{21}$$

In equation (19), $\boldsymbol{Z_t}$ is an unobservable identically, independently distributed (i.i.d) process that follow varying probability distributions and for this dissertation the focus will be on the Gaussian and Student-t including their skewed counterparts the skewed normal and skewed Student-t. For a Gaussian distribution, $\boldsymbol{z_t} \sim \boldsymbol{N}\,(\boldsymbol{0}, \boldsymbol{I})$. For the Student-t, $\boldsymbol{Z_t} \sim t_{\upsilon}(\upsilon)$, where υ represents degrees of freedom. Hansen (1994) proposes a skewed Student t - distribution where $\boldsymbol{Z_t} \sim t_{\upsilon}(\, \upsilon, \xi)$, and υ still represents degrees of freedom and ξ is an asymmetry parameter that is sometimes referred as the kurtosis or skewness coefficient. The functions' density can be mathematically represented as a follows:

$$f(z) = \begin{cases} bc\left(1 + \frac{1}{\upsilon - 2}\left(\frac{bz + a}{1 - \xi}\right)^2\right)^{-(\upsilon+1)/2} & for\ z < -\frac{a}{b} \\ bc\left(1 + \frac{1}{\upsilon - 2}\left(\frac{bz + a}{1 + \xi}\right)^2\right)^{-(\upsilon+1)/2} & for\ z \geq -\frac{a}{b} \end{cases} \tag{22}$$

In equation (22), $2 < \upsilon < \infty; -1 < \xi < 1$. By making $\xi = 0$ the density becomes that of a Student t and when υ is high (or close to ∞) the density becomes that of Gaussian. The constants a, b and c above can be represented as follows:

$$a = 4\xi c\ \frac{\upsilon - 2}{\upsilon - 1}$$

$$b^2 = 1 + 3\xi^2 - a^2$$

$$c = \frac{\Gamma\left(\frac{\upsilon + 1}{2}\right)}{\left(\sqrt{\pi(\upsilon - 2)}\ \Gamma\left(\frac{\upsilon}{2}\right)\right)}$$

In the definitions of a, b and c, $\Gamma(.)$ represents a Gamma function. The three density functions of $\boldsymbol{Z_t}$ have a zero mean and unit variance, that is $\boldsymbol{E(Z_t) = 0\ \ and\ E(Z_t Z_t^T) = I}$,where $\boldsymbol{I}$ represents an identity matrix with ones as on and off diagonals elements enabling $\boldsymbol{\varepsilon_t}$ to have the following distribution quantalities:

$$\boldsymbol{E(\varepsilon_t) = 0}\ and\ Cov(\boldsymbol{\varepsilon_t}) = \boldsymbol{H_t}$$

$$\boldsymbol{H_t = D_t R_t D_t}$$

$\boldsymbol{D_t}$ is an m by m diagonal matrix of conditional standard deviations of $\boldsymbol{\varepsilon_t}$at time t.

$$\boldsymbol{D_t} = diag(\boldsymbol{h_{11,t}^{\frac{1}{2}}}, \dots, \boldsymbol{h_{mm,t}^{\frac{1}{2}}})$$

Where:

- $\boldsymbol{h_{iit}^{\frac{1}{2}}}$ above is a conditional standard deviation modelled using a univariate GARCH model

- $\boldsymbol{R_t}$ is an m by m conditional symmetrical correlation (of quasi-correlations) matrix of $\boldsymbol{\varepsilon_t}$ at time *t*. There are numerous ways to define $\boldsymbol{R_t}$ this dissertation adopts the approach by Engle (2002a)

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

  - where for any vector **X**, **diag** (**X**) is an operator that creates a diagonal matrix using the elements of **X**

$$\boldsymbol{Q_t = (1 - \alpha_1 - \alpha_2)\bar{R} + \alpha_1 \bar{\varepsilon}_{t-1} \bar{\varepsilon}^T{}_{t-1} + \alpha_2 Q_{t-1}}$$

  - Each element in $\boldsymbol{R_t}$ can be expressed as follows (q ∈ $\boldsymbol{Q_t}$):

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$$

- $\boldsymbol{\alpha_i, i} \in [\boldsymbol{1, 2}]$ are non-negative scalar parameters that ensure that $\boldsymbol{Q_t}$ (hence $\boldsymbol{R_t}$) remains positive definitive and for stationarity purposes have a constraint that $(\boldsymbol{\alpha_1 + \alpha_2}) < \boldsymbol{1}$

- $\boldsymbol{\bar{\varepsilon}_t}$ is a vector of standardised residuals and has each element defined as follows:

$$\bar{\varepsilon}_{i,t} = \frac{\varepsilon_{i,t}}{(h_{it}^{1/2})^2} = \frac{\varepsilon_{i,t}}{\sigma_{it}} \qquad (23)$$

- $\boldsymbol{\bar{R}}$ is a symmetric matrix representing the unconditional mean of $\boldsymbol{Q_t}$ and is made of weighted average of the unconditional variance–covariance matrix of the estimators (VCE) of the standardised residuals.

$\boldsymbol{H_t^{1/2}}$ can be found using the Cholesky factorisation of $\boldsymbol{H_t}$. The above model is a VAR (p) – Dynamic Conditional Correlation (DCC) GARCH. The DCC-GARCH can be estimated using a quasi-maximum likelihood estimator (QLME) but depicts dependence using linear conditional correlation that is expected to have a similar evolving pattern based on the scalar parameters $\boldsymbol{\alpha_1} and\ \boldsymbol{\alpha_2}$; and that constituent marginal univariates series share similar distributional attributes. The component marginal volatilities and correlation of the DCC GARCH can be estimated separately, though they will still be under similar dynamics, by breaking the joint likelihood and this procedure, known as the two-step estimation, can be useful when dealing with a fairly large number of variables. The two-step estimation is thematically applied, using the inference for margin approach, by coupling or jointly modelling each univariate volatility model's distribution function using a copula and describing the resulting joint behaviour using a copula-DCC-GARCH model. The ensuing subsection introduce measures of dependence that are useful in gauging the level of association in data that is not normally distributed and are used in extensively in the analysis of the returns data and in joint dependence intra-economy.

3.3 Measures of Dependence

This sub-section introduces metrics that are used in assessing whether there is an association amongst sampled variables. Association amongst variables is quantified by various dependence metrics that are preferred and used based on data transformation sensitivity, computational and interpretation ease. In a bivariate case, random variables $\{r_x, r_y\}$, with a distribution function, F_i, are considered independent if $F_{xy}(r_x, r_y) = F_x(r_x)F_y(r_y)$, that is their joint function is a result of the product of each marginal function and this property is extendable to higher dimensions. Properties such as computational convenience, symmetry, normalisation and interpretability make the Pearson correlation coefficient to be a well-known and used measure of linear association for elliptically distributed data. The Pearson linear correlation coefficient between two variables at time t, $\{r_{x_t}, r_{y_t}\}$, is mathematically expressed in equation (24) below and is based on the assumption that the marginal variables' covariance structure, $Cov(r_{x_t}, r_{y_t}) = E(r_{x_t}, r_{y_t}) - E(r_{x_t})E(r_{y_t})$, exists.

$$\rho_P = \frac{Cov(r_{x_t}, r_{y_t})}{\sqrt{Var(r_{x_t})Var(r_{y_t})}} \tag{24}$$

From equation (24), it is observable that the variance-covariance structure is critical when assessing the association of variables and that a correlation coefficient of zero (from

$Cov\left(r_{x_t}, r_{y_t}\right) = 0$) would infer independence or non-existence of dependence, which is not always factual. An example often shared to show some of the shortcomings of linear correlation is that of standard normally distributed random variables $x \ and \ y = x^2$ which are uncorrelated, non-linearly dependent and from an elliptical distribution. Generally, the linear correlation coefficient as a measure of association is:

- Dependent on the distributional properties of the marginals.
- Exists when the second moment exists and is finite.
- Not invariant under non-linear transformations.

If a data series can be shown to be not normally distributed or skewed, measuring dependence would require the usage of a non-parametric rank and tail based measures of association to infer dependence in order to bypass the short-comings of the Pearson correlation coefficient. Such dependence metrics include Kendall's tau (ρ_τ), Spearman's rho (ρ_s) and tail dependence coefficient measures that are used in assessing conditional risk that arise from joint tail behaviour beyond certain thresholds. For this dissertation, focus will be on Kendall's tau as a measure of association and it is defined as the difference between the probabilities of concordance and discordance which well fits the purpose of this dissertation of assessing relation amongst specific assets. Two random observations (r_{x_i}, r_{y_i}) and (r_{x_j}, r_{y_j}) drawn from a two dimensional vector (r_x, r_y) are concordance if the product of their pairwise difference $(r_{x_i} - r_{x_j})\,(r_{y_i} - r_{y_j}) > 0$ and discordance if $(r_{x_i} - r_{x_j})\,(r_{y_i} - r_{y_j}) < 0$. A more formal definition of Kendall's ρ_τ is expressed in equation (25):

$$\rho_\tau = P\left(\left(r_{x_i} - r_{x_j}\right)\left(r_{y_i} - r_{y_j}\right) > 0\right) - P\left(\left(r_{x_i} - r_{x_j}\right)\left(r_{y_i} - r_{y_j}\right) > 0\right) \qquad (25)$$

The Kendall's ρ_τ metric is used to describe the dependence structure as it is independent of distribution class and can be expressed in terms of the copula functions $C_i, i \in \{1,2\}$ (as defined in Definition 3.1), as follows:

$$\rho_\tau = 4\int_0^1 \int_0^1 C_1(u_x, u_y) \; d\, C_2(u_x, u_y) - 1 \qquad (26)$$

Kendall's ρ_τ has the following a relationship with Pearson correlation (specifically for the Student t and Gaussian innovation assumptions used in this dissertation):

$$\rho_\tau = \frac{2}{\pi} arcsin(\rho_P) \quad (27)$$

3.3.1 Probability Integral Transformation

The PIT process is used to transform any continuous distribution function into a standard uniform variable. The process exists on the basis that, if a random variable X has a continuous distribution function F, then F(X) is a standard uniform random variable, that is F(X) ~ Unif (0,1). The converse of the PIT states that, for a random variable U ~ Unif (0,1) and distribution function F, $F^{\leftarrow}(U) \sim F$, where $F^{\leftarrow}$ is a quantile function for all distributions, a generalised inverse for increasing functions and is also equivalent to a normal inverse function , F^{-1}, when considering strictly increasing distributions. The PIT process is performed to ensure comparability of distributions from varying marginal families. Hence, if the PIT of continuous random variables $X \; and \; Y$ is define as $U = F(X) \; and \; V = G(Y)$, for any given continuous distinct non-unique distribution functions F and G, respectively, it follows that both U and $V$are uniformly distributed random variables and their joint function $W(U, V)$ is equivalent to the copula of (X, Y) (Fan and Patton, 2014). For this dissertation's specific case, the PIT process allows for measuring dependence structure by using marginals' standardized residuals as pseudo-uniform variables and substituting the empirical data in the modelling of copula parameters. The conversion of standardised residuals into pseudo-uniform variables is done parametrically for the DCC GARCH and semi-parametrically for the GARCH Copula.

3.3.2 GARCH - Copula

Chen and Fan (2006) are amongst some of the authors that propose the semiparametric method mentioned in sub-section 3.3.1. The semiparametric method estimates a GARCH-copula using pseudo observations that are derived from transforming component marginal models' standardised residuals into pseudo-uniformly distributed variables $\{\widehat{\boldsymbol{U}}_i\}_{i=1}^{d} = \{\widehat{U}_{1,j}, \dots, \widehat{U}_{i,j}\}, j = 1, \dots, n$ where n is the number of observations in the j^{th} margin. According to Embrechts and Hofert (2013) and Chen and Fan (2006) each element $\widehat{U}_{i,j}$ represents the i^{th} ranking, R_{ij}, of the distribution function (DF) amongst $\{X_{ij}\}_{j=1}^{n}$ and can be defined as follows:

$$\widehat{U}_{i,j} = \frac{n}{n+1}\,\widehat{F}_{n,i}\big(X_{i,j}\big) = \frac{R_{ij}}{n+1} \tag{28}$$

where $\widehat{F}_{n,i}$, $i \in \{1, \dots d\}$, is an empirical CDF estimated as follows:

$$\widehat{F}_n(X_i) = \frac{1}{n}\sum_{k=1}^{n} \mathbf{1}\,(X_k \le X_i) \tag{29}$$

A copula indicating the dependence structure of the GARCH estimated marginals is measured for each economy giving a view or the level of association or its structure amongst the sampled variables. Further, the dependence measure is initially tested if it is time-varying or can be treated as static based on a test by Bücher et al.(2014). The test detects if there is a change-point or nonconsistency in the distribution function (DF) of a d-dimensional vector of continuous marginals $\{X_i\}_{i=1}^{d}$ and the test's null hypothesis is defined below against an alternative hypothesis of the nonconsistency in the distribution function.

$$H_{null} : \exists \;\; DF \;\; F = (F_1, F_2, \dots, F_d) \; such \; that \; \{X_i\}_{i=1}^{d} \; have \; DF \;\; F$$

The following section introduces a copula-based extension to the DCC GARCH model that is expected to overcome some previously mentioned drawbacks such as disallowing for modelling of univariates using variance models from varying GARCH families.

3.4 Copula based DCC-GARCH Model

A copula can be defined as a function that relates or couples a multivariate joint distribution function with its marginal distributions that are uniformly distributed (Nelsen, 1999). Copulas allow for viewing of a multivariate distribution's copula (dependence) and marginal structure without the need of imposing distributional properties on the joint and marginal distributions. A k – dimensional copula Ç can be mathematically defined as below.

Definition 3.1: k –Dimensional Copula.

A function Ç defined as:

$$Ç : [\mathbf{0}, \mathbf{1}]^{\boldsymbol{k}} \to [\mathbf{0}, \mathbf{1}]$$

is a k – dimension copula if for each $\boldsymbol{u_i}\sim$ a marginal distribution in $[\mathbf{0}, \mathbf{1}]$, satisfies the following properties:

1) $Ç\,(\boldsymbol{u_1}, \boldsymbol{u_2}, \dots, \boldsymbol{u_k}) = \mathbf{0} \quad \boldsymbol{for\ any}\ \boldsymbol{u_i} = \mathbf{0}, \boldsymbol{i} \in [\mathbf{1}, \dots, \boldsymbol{k}]$

2) $Ç\,(\boldsymbol{u_1}, \boldsymbol{u_2}, \dots, \boldsymbol{u_k})$ is non-decreasing, strictly and n-increasing for each element $\boldsymbol{u_i}, \boldsymbol{i} \in [\mathbf{1}, \dots, \boldsymbol{k}]$

3) $Ç\,(\boldsymbol{u_1}, \boldsymbol{u_2},, \dots, \boldsymbol{u_i}, \dots, \boldsymbol{u_k}) = \boldsymbol{u_i}$ by setting all $\boldsymbol{u_j} = \mathbf{1}$ for each $\boldsymbol{j} \neq \boldsymbol{i}\ \boldsymbol{and}\ \boldsymbol{i}, \boldsymbol{j} \in [\mathbf{1}, \dots, \boldsymbol{k}]$

4) For each $\boldsymbol{a_i} \leq \boldsymbol{b_i}$, $\boldsymbol{P}(\boldsymbol{u_1} \in [\boldsymbol{a_1}, \boldsymbol{b_1}], \dots, \boldsymbol{u_k} \in [\boldsymbol{a_k}, \boldsymbol{b_k}])$ must be non-negative and

$$\sum_{\boldsymbol{i_1}}^{\mathbf{2}} \cdots \sum_{\boldsymbol{i_k}}^{\mathbf{2}} (-\mathbf{1})^{\sum_{j=1}^{k} i_j}\ Ç\left(\boldsymbol{u_{1,i_1}}, \dots, \boldsymbol{u_{k,i_k}}\right) \geq \mathbf{0}$$

Copulas as an association measure can be classified into three main broad categories and measures which are concordance, independence and discordance. For the detailed description and example using a case of k = 2 random variables u_1 and u_2, with each $u_i \sim Unif\ (0,1)\ \ i\ \in\ [1,2]$ and a copula function Ç. Concordance can be regarded as a case of perfect positive dependence, discordance occurs when $u_2 = 1 - u_1$. Concordance ($Ç_{Con}$), independence ($Ç_{Ind}$) and discordance ($Ç_{Dis}$) copulas are expressed respectively in the equations below and can be extended to any k-dimensional copula.

$$Ç_{Con}\ (u_1, u_2) = min(u_1, u_2) \tag{30}$$

$$Ç_{Ind}\ (u_1, u_2) = u_1 \cdot u_2 = \prod_{i=1}^{2} u_i \tag{31}$$

$$Ç_{Dis}\ (u_1, u_2) = u_1 + u_2 - 1 \tag{32}$$

Sklar (1959) and the reference therein introduces the theorem defined below that relates an n-dimensional copula with its joint distribution.

Theorem 3.1: Let $\boldsymbol{H} = \boldsymbol{F_{123\ldots n}}$ be an n-dimensional joint distribution function with margins $\boldsymbol{F_1}, \boldsymbol{F_2}, \ldots, \boldsymbol{F_n}$. Then there exists an n-copula Ç such that for all $\boldsymbol{x} \in (\ \mathbb{R}^{\boldsymbol{n}}\ \cup\ \{\pm\infty\}\ )$

$$\boldsymbol{H}\ (\boldsymbol{x_1}, \boldsymbol{x_2}, \boldsymbol{x_3}, \ldots, \boldsymbol{x_n})\ =\ Ç\ (\boldsymbol{F_1}(\boldsymbol{x_1}), \boldsymbol{F_2}(\boldsymbol{x_2}), \ldots, \boldsymbol{F_n}(\boldsymbol{x_n})) \tag{33}$$

The converse of the above theorem is that if Ç is an n-copula and $\boldsymbol{F_1}, \boldsymbol{F_2}, \ldots, \boldsymbol{F_n}$ are marginals then H (.) as defined above is a joint distribution function with marginals $\boldsymbol{F_1}, \boldsymbol{F_2}, \ldots, \boldsymbol{F_n}$. If $\boldsymbol{F_1}, \boldsymbol{F_2}, \ldots, \boldsymbol{F_n}$ are continuous then Ç is unique and determined on $\boldsymbol{RanF_1\ x\ RanF_2\ x \ldots x\ RanF_n}$ (Nelsen, 1999). Each $\boldsymbol{F_i}, \boldsymbol{i}\ \in\ [\boldsymbol{1}, \boldsymbol{n}]$ can have unique distributional attributes.

When $F_i^{(-1)}, i \in [1, n]$ is considered as a quasi-inverse of $F_i, i \in [1, n]$, the extension of the immediate above equation can be expressed as follows:

$$Ç\,(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) = H\,(F_1^{(-1)}(x_1), \ldots, F_n^{(-1)}(x_n)) \tag{34}$$

The above theorem uses cumulative density function (CDF) and can also be represented using probability density functions (PDF) when the assumption of function continuity and differentiability is considered (Patton, 2006; Thanh and Barassi, 2014).

$$f_{12\ldots n}\,(x_1, \ldots, x_n) = \prod_{a=1}^{n} f_a\,(x_a)\; Ç\,(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) \tag{35}$$

From the previous equation,

$$Ç\,(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) = \frac{f_{12\ldots n}\,(x_1, \ldots, x_n)}{\prod_{a=1}^{n} f_a\,(x_a)} \tag{36}$$

Also, the log-likelihood function of the density function can be derived as:

$$\log f_{12\ldots n}(x_1, \ldots, x_n) = \sum_{a=1}^{n} \log[f_a(x_a)] + \log\left[Ç\left(F_1(x_1), \ldots, F_n(x_n)\right)\right] \tag{37}$$

The equation (37) above separates the log-likelihood function of a joint density into its copula log-likelihood function and log-likelihood of the marginals and in this specific case the volatility GARCH estimated marginals. For this dissertation, the elliptical family of Gaussian and Student t copulas are used in conjunction with the conditional correlation matrix parameters, R_t and $\theta = (\propto, \delta)$ from the above mentioned DCC-GARCH model. The density of a Gaussian and Student-t copula are expressed respectively in the equations below:

$$c(\bar{\varepsilon}_{i,t} \mid R_{i,t}) = \left|R_{i,t}\right|^{-\frac{1}{2}} e^{-\frac{1}{2}\bar{\varepsilon}_{i,t}{}^{T}(R_{i,t} - I)\,\bar{\varepsilon}_{i,t}} \tag{38}$$

Where **I** above is an identity matrix.

$$c(\bar{\varepsilon}_{i,t} | \, R_{i,t} \, , \tau) \; = \; \frac{\Gamma\left(\frac{\tau+k}{2}\right)\left(\Gamma\left(\frac{\tau}{2}\right)\right)^{k}\left(1 \; + \; \frac{\bar{\varepsilon}_{i,t}{}^{T} R_{i,t} \, \bar{\varepsilon}_{i,t}}{\tau}\right)^{-\frac{\tau+k}{2}}}{\left|R_{i,t}\right|^{\frac{1}{2}} \left(\Gamma\left(\frac{\tau+1}{2}\right)\right)^{k} \Gamma\left(\frac{\tau}{2}\right) \prod_{i\,=\,1}^{k}\left(1 \; + \; \frac{\bar{\varepsilon}_{i,t}{}^{2}}{\tau}\right)^{-\frac{\tau+1}{2}}} \tag{39}$$

Where $\Gamma(.)$ and τ represent a Gamma distribution function and degrees of freedom, respectively.

From joining the above equations, below is a representation of the seperated loglikelihood density into a copula and volatility marginals' loglikelihood.

$$\begin{aligned} \mathcal{L}_{i,t}(\theta_{i,t})^{\,Gaussian} &= -\frac{1}{2}\left(2log(2\pi) \; + \; log\left|D_{i,t}\right|^{2} \; + \; \varepsilon_{i,t}{}^{T} D_{i,t}^{-2} \varepsilon_{i,t}\right) \\ &+ \; -\frac{1}{2}\left(log\left|R_{i,t}\right| \; + \bar{\varepsilon}_{i,t}{}^{T} R_{i,t}^{-1} \, \bar{\varepsilon}_{i,t} \; - \; \bar{\varepsilon}_{i,t}{}^{T} \bar{\varepsilon}_{i,t}\right) \end{aligned} \tag{40}$$

$$\begin{aligned} \mathcal{L}_{i,t}(\theta_{i,t}, \tau)^{\,Student\,t} &= \; log\frac{\Gamma\left(\frac{\tau+1}{2}\right)}{\Gamma\left(\frac{\tau}{2}\right)} - \frac{1}{2}\left(log(\,\pi(\tau \; - 2)) + log\left|D_{i,t}\right|^{2} + (\tau + 1) \, log\left(1 + \frac{\varepsilon_{i,t}{}^{2}}{\tau - 2}\right)\right) \\ &- \; log\frac{\Gamma\left(\frac{\tau+k}{2}\right)}{\Gamma\left(\frac{\tau}{2}\right)} - \; k \, log\frac{\Gamma\left(\frac{\tau+1}{2}\right)}{\Gamma\left(\frac{\tau}{2}\right)} - \frac{\tau+k}{2} log\left(1 \; + \; \frac{\bar{\varepsilon}_{i,t}{}^{T} R_{i,t} \, \bar{\varepsilon}_{i,t}}{\tau}\right) - log\left|R_{i,t}\right| \; - \; \frac{\tau+1}{2} \sum_{i=1}^{k}\left(1 \; + \; \frac{\bar{\varepsilon}_{i,t}{}^{2}}{\tau}\right) \end{aligned} \tag{41}$$

Where $\Gamma(.)$ and τ represent a Gamma distribution function and degrees of freedom, respectively.

3.5 Causality

Studying causality amongst the sampled variables will further give insights to the degree at which information flows between variables in an economy. Causality in returns and volatility are measured using the premise of a variables' historical values being assessed for significance in the modelling vector AR and ARMA models and is based on the added predictive capability from the inclusion of each variable's innovations.

3.5.1 Conditional Causality in Mean

For stochastic processes, $\boldsymbol{X_t}, \boldsymbol{Y_t}$ and $\boldsymbol{Z_t}$, according to Granger (1969), $\boldsymbol{X_t}$ Granger–cause $\boldsymbol{Y_t}$, if the past values of $\boldsymbol{X_t}$ better enable the prediction $\boldsymbol{Y_t}$ beyond the value derived from using its own past values. The better prediction of $\boldsymbol{Y_t}$ is achieved when the variance of $\boldsymbol{Y_t}$ given its own past values is made lesser by including the past values of $\boldsymbol{X_t}$. A joint effect from a common stochastic process $\boldsymbol{Z_t}$ can be significantly contributing to the G-causal inference between $\boldsymbol{Y_t}$ and $\boldsymbol{X_t}$. The common $\boldsymbol{Z_t}$ effect can be conditioned out by including it in each stochastic process when assessing the influence each has on the other. The generic variables can represent groupings of variables, in this dissertation where for example $\boldsymbol{X_t}, \boldsymbol{Y_t}\ and\ \boldsymbol{Z_t}$ can respectively represent commodities (oil and gold), exchange rates and stock markets at time t. From the description of a VAR (p) model the following equation can be derived.

$$\begin{pmatrix} \boldsymbol{r_t^C} \\ \boldsymbol{r_t^{ER}} \\ \boldsymbol{r_t^{SM}} \end{pmatrix} = \boldsymbol{\beta_0} + \sum_{i=1}^{p} \boldsymbol{\beta_{t-i}} \begin{pmatrix} \boldsymbol{r_{t-i}^C} \\ \boldsymbol{r_{t-i}^{ER}} \\ \boldsymbol{r_{t-i}^{SM}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon_t^C} \\ \boldsymbol{\varepsilon_t^{ER}} \\ \boldsymbol{\varepsilon_t^{SM}} \end{pmatrix} \tag{42}$$

In equation (42), $\boldsymbol{r_t^C}, \boldsymbol{r_t^{ER}}\ and\ \boldsymbol{r_t^{SM}}$ represent commodities' price, exchange rates' and stock market index returns, respectively and their error terms $\boldsymbol{\varepsilon_t^C}$, $\boldsymbol{\varepsilon_t^{ER}}$ and $\boldsymbol{\varepsilon_t^{SM}}$. $\boldsymbol{\beta}$ is a matrix depicting the effect of the past values of each variable to the value at time t and can be represented as follows:

$$\boldsymbol{\beta} = \begin{pmatrix} \boldsymbol{A^{C-C}} & \boldsymbol{A^{E-C}} & \boldsymbol{A^{S-C}} \\ \boldsymbol{A^{C-E}} & \boldsymbol{A^{E-E}} & \boldsymbol{A^{S-E}} \\ \boldsymbol{A^{C-S}} & \boldsymbol{A^{E-S}} & \boldsymbol{A^{S-S}} \end{pmatrix}$$

Where, depending on variables of interest, for example $\boldsymbol{A^{E-C}}$ could be equivalent to the impact past changes in exchange rate prices have on commodity price changes. Should the variable of interest be that of returns in exchange rates $\boldsymbol{r_t^{ER}}$, the following equation can be deduced:

$$\boldsymbol{r_t^{ER\,(Full\,model)}} = \boldsymbol{\beta_{01}^{ER}} + \sum_{\boldsymbol{i=0}}^{\boldsymbol{p}} (\boldsymbol{A_{t-i}^{C-E}}\, \boldsymbol{r_{t-i}^{C}} + \boldsymbol{A_{t-i}^{E-E}}\, \boldsymbol{r_{t-i}^{ER}} + \boldsymbol{A_{t-i}^{S-E}}\, \boldsymbol{r_{t-i}^{SM}}) + \boldsymbol{\varepsilon_t^{ER}} \tag{43}$$

$\boldsymbol{\beta_{01}^{ER}}$ represents a vector of constants. To test for stock market changes as being conditionally G-causal to exchange rate, the above can also be represented in a reduced form that only uses its past value that is inclusive of the conditioned variable being tested for causality which can be commodities in this example.

$$\boldsymbol{r_t^{ER\,(reduced\,model)}} = \boldsymbol{\beta_{02}^{ER}} + \sum_{\boldsymbol{i=0}}^{\boldsymbol{p}} (\boldsymbol{A_{t-i}^{C-E}}\, \boldsymbol{r_{t-i}^{C}} + \boldsymbol{A_{t-i}^{E-E}}\, \boldsymbol{r_{t-i}^{ER}}) + \boldsymbol{\varepsilon_t^{ER}} \tag{44}$$

$\boldsymbol{\beta_{02}^{ER}}$ represents a vector of constants. The conditional G-causality test uses the maximum likelihood theory to check for the better model between the full and reduced model for the example above the test can be expressed in the following manner (Barnett and Seth, 2014):

$$ln\left(\frac{\left|cov(\varepsilon_t^{exchange\ rate})^{reduced\ model}\right|}{\left|cov(\varepsilon_t^{exchange\ rate})^{Full\ model}\right|}\right) \tag{45}$$

The test in equation (31), for the example, uses the following null hypothesis:

$$H_{null}: A_{t-i}^{S-E} = 0\ , for\ i\ \in\ \{1, \dots, p\} \tag{46}$$

The test in equation (46) is based on a null hypothesis of $\chi^2_\alpha(d_r)$ and alternative $\chi^2_\alpha(d_f, v)$ where $d_r\ and\ d_f\ are$ the dimensions of all variables in the reduced and full models respectively and v difference between number of variables m and p, (m - p) , with p being number of significant lags in the VAR system.

3.5.2 Non-causality in Variance

Hafner and Herwartz (2006) introduce a Lagrange Multiplier (LM) based test that utilises univariate GARCH stylised second moments to infer noncausality in variance. The null hypothesis of the test can be expressed informally as checking if there's no change in the conditional variance when including past values of both variables of interest and when excluding the past values of one of the variables. Mathematically expressed, for $i, j \in \{1, \ldots, \mathbb{N}\}\ and\ i \neq j,$ the test uses the following null hypothesis:

$$H_{null}: Variance(\varepsilon_{i,t} \mid X_{t-1}) = Variance(\varepsilon_{i,t} \mid \tilde{X}_{t-1}) \quad (47)$$

Where X_{t-1} and $\tilde{X}_{t-1}$ represent information set at time t-1 based on past values of variable of interest and $\tilde{X}_{t-1}$ is an altered version of X_{t-1} as it excludes the variance of stochastic processes which is being queried for its variance noncausality. The test in equation (47) applies the definition of standardised residuals expressed in equation (23):

$$\varepsilon_{i,t} = \bar{\varepsilon}_{i,t}\sqrt{g_t \sigma_{it}{}^2}$$

where

$$g_t = 1 + z_{jt}{}^T \pi$$

$$z_{jt}{}^T = \left(\bar{\varepsilon}_{j,t}, \sigma_{jt}{}^2\right)^T$$

where:

$\bar{\varepsilon}_{j,t}$ and $\sigma_{jt}{}^2$ represent the standardised residuals and conditional variance of $\tilde{X}_{t-1}$.

To make conclusions in (47) the test is based on an $\hat{\lambda}_{LM}$ statistic that follows asymptotic chi-square distribution with 2 degrees of freedom (the value is based on the number of misspecification indicators in ${z_{jt}}^T$) and is equivalent to testing the following null hypothesis (Hafner and Herwartz, 2006):

$$H_{null}: \pi = 0 \tag{48}$$

Chang and Mcaleer (2017) argue that the alternative hypothesis of the test in (34) is not based on a stochastic process and offer an alternative methodology that is in line with the initial idea similar to that of 3.5.1 that is based on prediction improvement as an implication of causality. The test by Chang and Mcaleer (2017) uses as an example a GARCH environment with two assets and the significance of either asset's past volatility as an indicator of second order and causality in variance.

3.6 Chapter Summary

This chapter mainly introduced the econometric framework to be used in responding to the research questions of section 1. The chapter initial dealt with how the sampled univariate marginals will each be modelled using an AR-GARCH model and how the dissertation focuses mainly on the standard GARCH, EGARCH and GJR GARCH models to achieve this outcome. The chapter also introduced the student t and Gaussian copulas which will be applied in coupling the marginals and assist in defining their joint behaviour for each economy. This section further introduced the causality approach that will be useful in understanding causality and the informational flow in the variance. The ensuing section introduces and discusses the data onto which the framework of the models outlined in the current chapter will be applied.

4 Empirical Data Description and Analysis

4.1 Data Description

This section of the dissertation introduces the times series data onto which the econometric models of Chapter 3 will be applied. The time series data consists of the logarithmic change of consecutive monthly spot and nominal prices of gold, crude oil, sampled economies' local currencies' exchange rate per USD (each converted to the prevailing month's nominal USD) and primary stock market's performance data. For each sampled economy or group of economies, the stock market's performance data will be represented using each country's domestic primary stock market's main index as a proxy to stock markets overall performance instead of other activity metrics such as traded volume, listed companies and overall market capital. Each of the sampled variables will be used in a logarithmic transformed form which is expressed in equation (49), with P_t and r_t representing the prevailing month's spot price and return at time *t*, respectively.

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{49}$$

The sample period used in this research spans between January 2000 and December 2019. Due to data availability, the inferences will only be made on data fitted in-sample (no out of sample period is created for predicting). The sampled period is of interest because it covers the 2008 global financial and European debt crises and includes some notable oil price slumps such as the one that occurred between 2014 and 2016. Monthly (end of period, where possible) returns are used as data points and this is to account for varying markets' operating times. Not all the chosen economic variables have data spanning the period of interest per economy. Hence, some of the conclusions and inferences are limited by data availability and structure within the sampled period. For example, economies such as Zambia (2012) and Egypt (2003) respectively re-denominated and changed the pegging structure of their domestic currencies; Ghana discontinued and replaced the domestic all share index with the GSE Composite in 2011; Angola did not have a domestic stock market and Ethiopia had a commodity exchange operating sampled period. Hence, the stock markets of Angola (Angolan Stock Exchange), Ethiopia (Commodity Exchange), Libya (Libyan

Stock Market) and Cameroon (Douala Stock Exchange) are not sampled in the study. The available start date of the stock market performance indices becomes the initial point to analyse the data and influences the number of data points or observations for each economy that has both a stock market and currency sampled otherwise all other countries have data observations throughout the sample period.

To select major African economies, countries are sampled based thematically on the World Bank's GDP global rankings approach, which ranks economies based on USD denominated version of each economy's annual gross domestic product. Over the sample period the AFDB's Socio Economic data points were used to check for each African economy's annual nominal GDP (in millions of USD) contributions to Africa's overall annual nominal GDP (GDP). A sample of the highest 20 ranking economies that accounted or contributed consistently for a significant (more than 80%) part of the African continent's total GDP over the sampled period is used. The visualisation, Figure 4.1, shows the GDP contribution per economy to the overall African annual GDP.

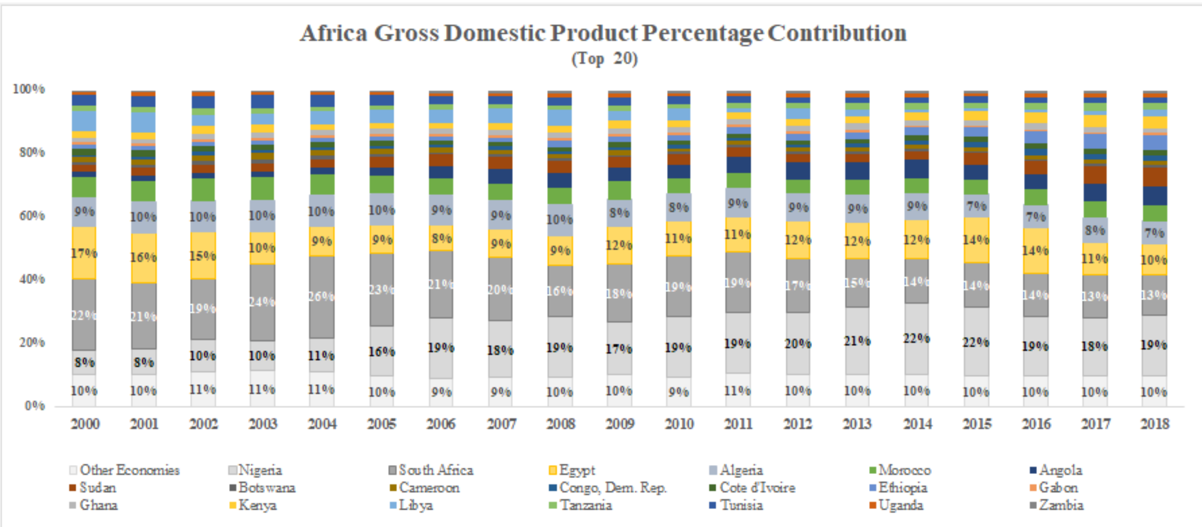

Figure 4.1: Annual Africa's GDP Contribution per African Economy

Data source: African Development Bank

Figure 4.1 shows a trend emanating from the highest and lowest GDP contributions overtime. The major economies Algeria, Egypt, Nigeria and South Africa have consistently had the highest contribution to the overall African GDP. The trend also shows growth in the level of contribution of Nigeria, 8% in the year 2000 to 19% in 2018. There is also a consistent (~10%) GDP contribution from unsampled economies that remains steady over time and this sample includes more than 30 African economies.

The data is sourced with assumed reliability and confidence from varying sources including International Monetary Fund's International Statistics, African Development Bank, Quandl, EIA (USA's energy information administrator), Botswana Stock Exchange, Egypt Stock Exchange, Algiers Stock Exchange, Nigeria Stock Exchange, Annual Reports Ghana, Johannesburg Stock Exchange, World Gold Council, Kenya's Capital Market Authority (CMA), Sanabelfs Securities and Iress. All the stock market indices are in local currency units (LCU) and represent the overall stock market. Due to data availability challenges, there are cases where a "blue chip" index is used instead of an overall market index. Crude oil and gold prices are in nominal USD and are not converted to their LCU prices to avoid high co-movement levels that would emanate from each commodity price being represented as a multiple of the LCU while itself being an independent variable, collinearity.

Within the sampled period, there are economies that were part of a regional economic and monetary union, and some were members of a regional stock exchange an example would be member countries of the West African Economic and Monetary Union (WAEMU) and Central African Economic and Monetary Community (CEMAC). The economic unions, in this context, allow for unsampled economies to be indirectly and directly part of the studied African economies hence increase the sample size onto which inferences can be applied. For instance, CEMAC member countries; Cameroon, Central African Republic, Republic of Congo, Chad, Equatorial Guinea and Gabon are part of the community that used, as an exchange currency the CFA Franc with BEAC as the central bank; whereas Benin, Burkina Faso, Côte d'Ivoire (Ivory Coast), Guinea-Bissau, Mali, Niger, Senegal and Togo used the CFA Franc with BCEAO as the central bank and are member countries of the Bourse Regionale des Valeurs Mobilieres (BRVM) stock market. Table 4.1 and Table 4.2, respectively, highlight the currency and stock market of each economy and, where it exists, the relationship some of the sampled economies' currencies and stock market have. The treatment applied would be to only analyse and apply a "blanket" inference to a group of economies that are part of an economic union.

Table 4.1 Currency of Sampled Economies

Economy	**ISO Code**	**Currency**
Algeria	DZD	Dinar
Angola	AOA	Kwanza
Botswana	BWP	Pula
Cameroon & Gabon [Members Not Sampled: Central African Republic, Congo, Chad & Equatorial Guinea]	XAF	Central African CFA Franc
Côte d'Ivoire [Members Not Sampled: Benin, Burkina Faso, Guinea-Bissau, Mali, Niger, Senegal &Togo]	XOF	West African CFA Franc
DR. Congo	CDF	Congolese Franc
Egypt	EGP	Pound
Ethiopia	ETB	Birr
Ghana	GHS	Cedi
Kenya	KES	Shilling
Libya	LYD	Dinar
Morocco	MAD	Dirham
Nigeria	NGN	Naira
South Africa	ZAR	Rand
Sudan	SDG	Pound
Tanzania	TZS	Shilling
Tunisia	TND	Dinar
Uganda	UGX	Shilling
Zambia	ZMW/ZMK	Kwacha

Table 4.2: The Stock Market Indices of Sampled Economies

Economy	**Stock Exchange (SE)**	**Sampled Index**	**Sample Start Date**
Algeria	Algerian SE (SGBV)	DZAIR	2008/01
Botswana	Botswana SE	Domestic Companies (BSEDCI)	2000/01
Egypt	Egyptian Exchange	EGX 30	
Ghana	Ghana SE	GSE Composite/ALSI	
Kenya	Nairobi SE	NSE 20 Share	
Tunisia	Bourse de Tunis	Tunindex	
Nigeria	Nigerian SE	All Share (NEASI)	
South Africa	Johannesburg SE	All Share (SALSI)	
Morocco	Casablanca SE	All Share (MASI)	2002/01
Côte d'Ivoire [Members Not Sampled: Benin, Burkina Faso, Guinea-Bissau, Mali, Niger, Senegal &Togo]	Bourse Regionale des Valeurs Mobilieres (BRVM)	BRVM Composite	2008/09
Sudan	Khartoum SE	Khartoum 30	2003/09
Tanzania	Dar es Salaam SE	All Share (TSEASI)	2006/11
Uganda	Uganda SE	All Share (USE)	2003/10
Zambia	Lusaka SE	All Share (LuASI)	2008/09

4.1.1 Data Overview

For each visual shown in sections 4.1.1.1 and 4.1.1.2, both the price and return level data points are presented over the sampled period. As mentioned in Chapter 3, only returns data in the form of a natural logarithm will be modelled and analysed. The visualisation of the data in the ensuing section will be to understand the behaviour of the returns (and end of period price) per variable over time. In the discussions, currency ISO codes will be used, instead of the actual name, to reference each economy's currency's exchange rate to the USA dollar direct quotation per month. From an overall view there is an observable trend that links both the price of a stock exchange and domestic currency, however, the trend isn't as clear when visualising commodities in relation to each economy's data. There is also an upward trend for most units of local currencies, indicating a general appreciation of the USD. Also observable in the price level data are certain events and regime changes, such as the 2016 move from a managed to a free-floating currency by Egypt. The returns data does not show any form of none-stationarity or trend but has some jumps and notable outliers. For most economies' return series, the 2007/2008 crisis did bring some notable change in volatility.

4.1.1.1 Commodities Data

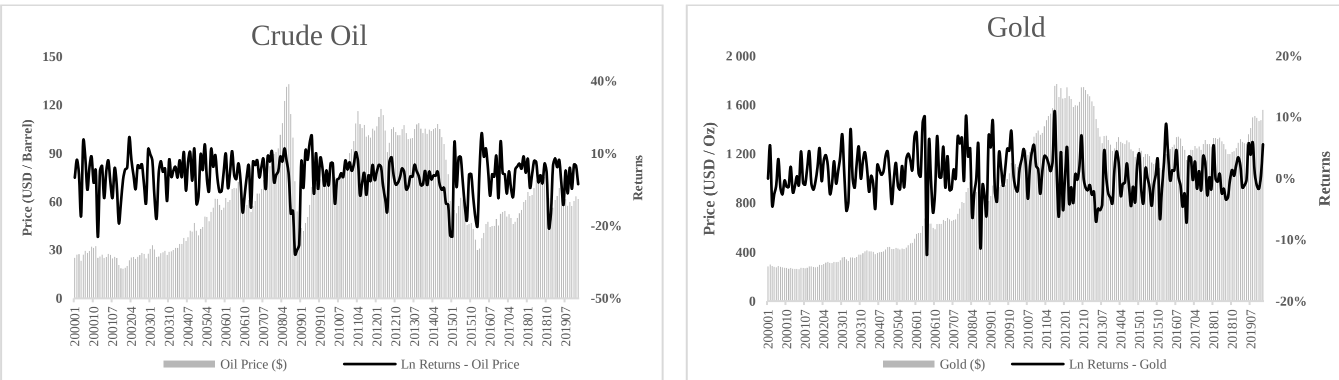

Figure 4.2: Crude Oil and Gold Monthly Prices and Returns from 2000 to 2019

Data source: IMF International Statistics, World Gold Council and EIA

4.1.1.2 Currency and Equities Market Data

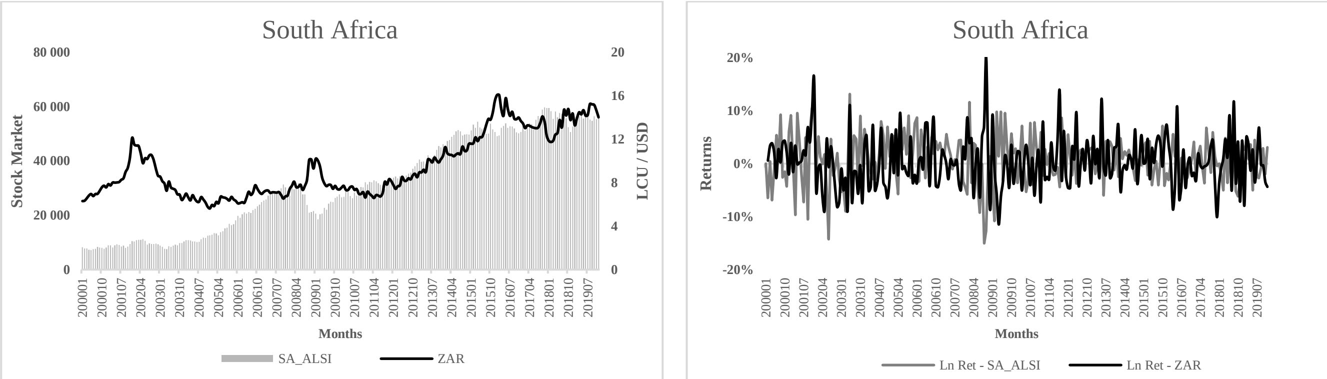

Figure 4.3: South Africa Stock and Currency Markets

Data source: IMF International Statistics, Johannesburg Stock Exchange and Iress

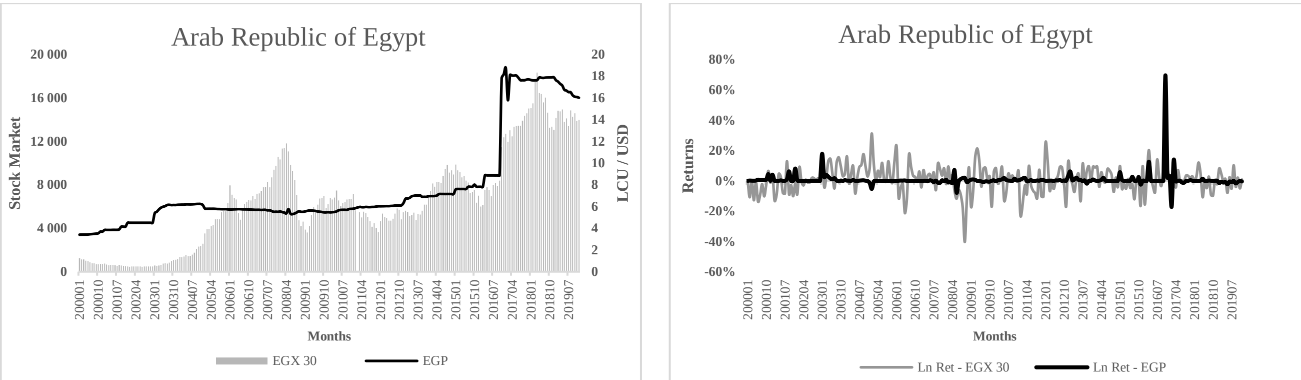

Figure 4.4: Egypt Stock and Currency Markets

Data source: IMF International Statistics and Egypt Stock Exchange

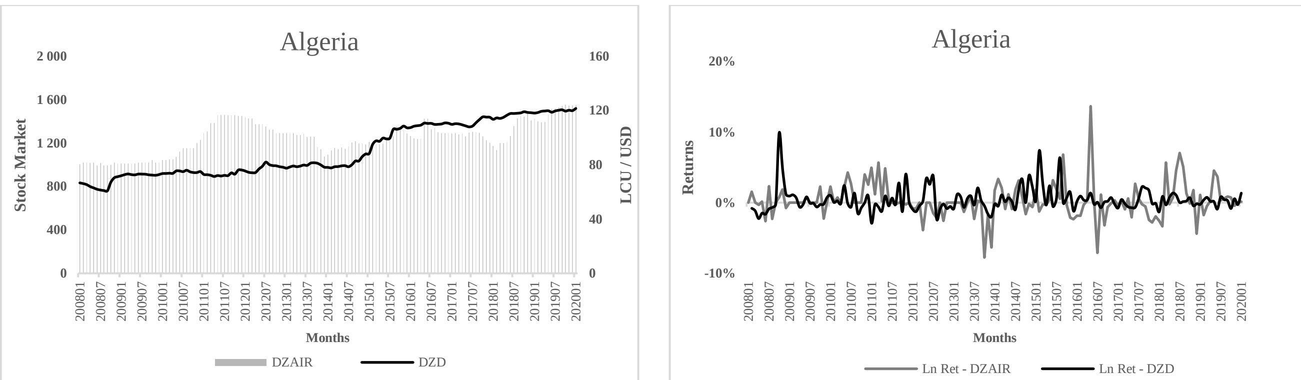

Figure 4.5: Algeria Stock and Currency Markets

Data source: IMF International Statistics and Algeria Stock Exchange

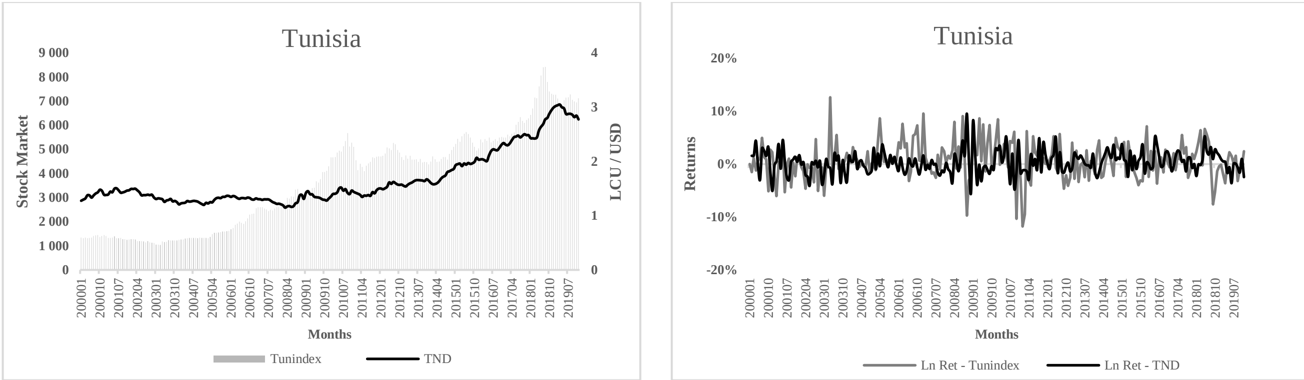

Figure 4.6: Tunisia Stock and Currency Markets

Data source: International Monetary Fund and Quandl

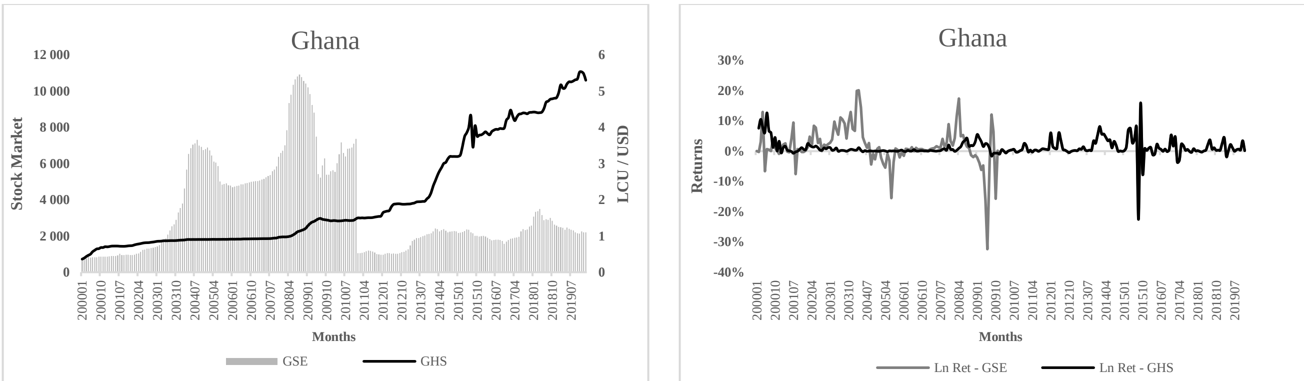

Figure 4.7: Ghana Stock and Currency Markets[3]

Data source: IMF International Statistics and Annual Reports Ghana's daily data

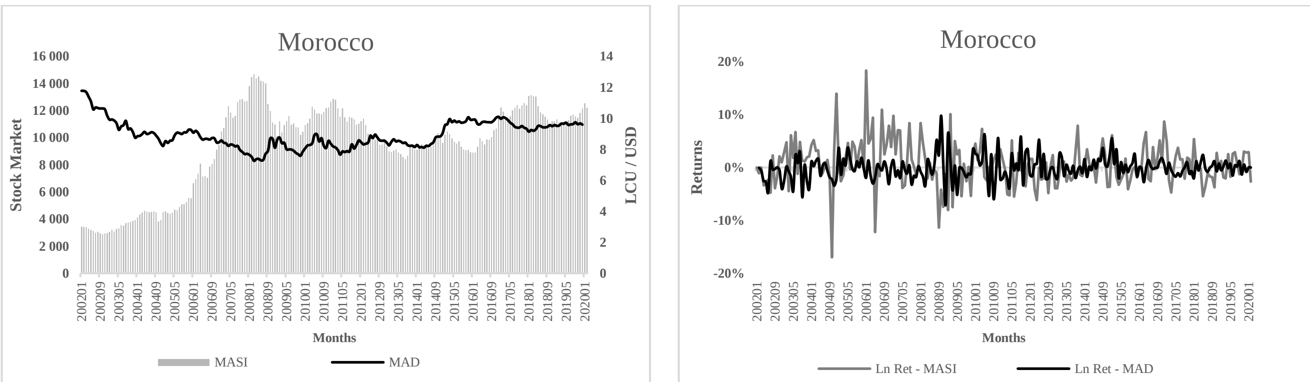

Figure 4.8 : Morocco Stock and Currency Markets

Data source: IMF International Statistics, Morocco Stock Exchange and Iress

[3] An arithmetic average between the changes at the end Ghana All Share and start of GSE Composite is used to join breaking point of the two indices.

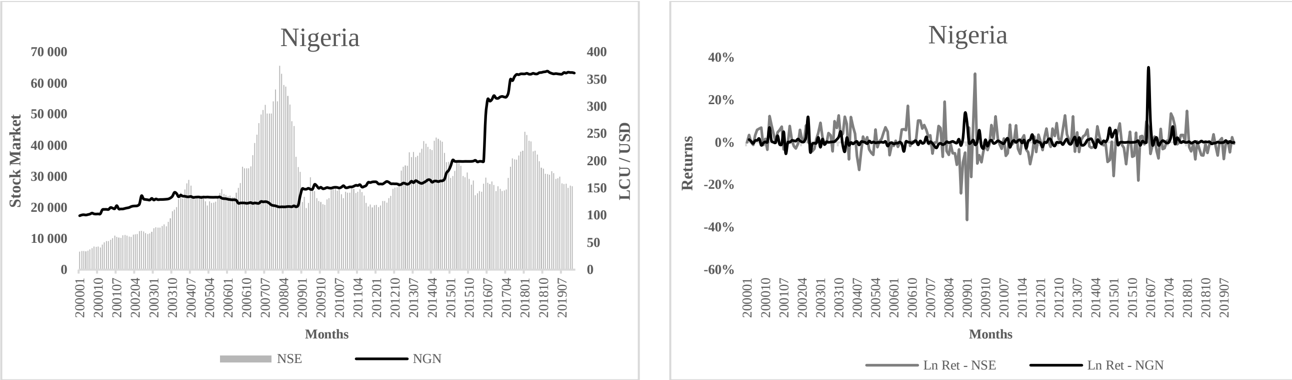

Figure 4.9: Nigeria Stock and Currency Markets

Data source: IMF International Statistics, Nigeria Stock Exchange and Iress

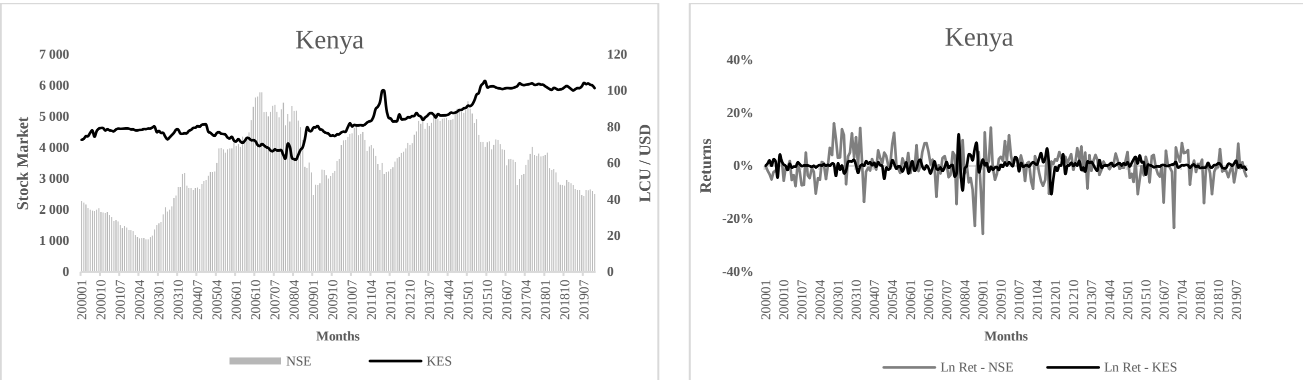

Figure 4.10: Kenya Stock and Currency Markets

Data source: IMF International Statistics, Kenya's Capital Market Authority and Iress

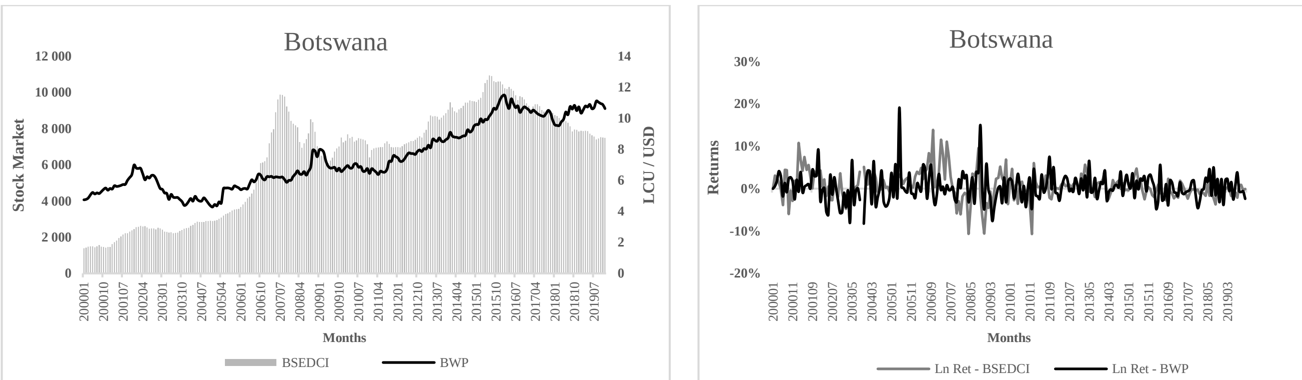

Figure 4.11: Botswana Stock and Currency Markets

Data source: IMF International Statistics, Botswana Stock Exchange

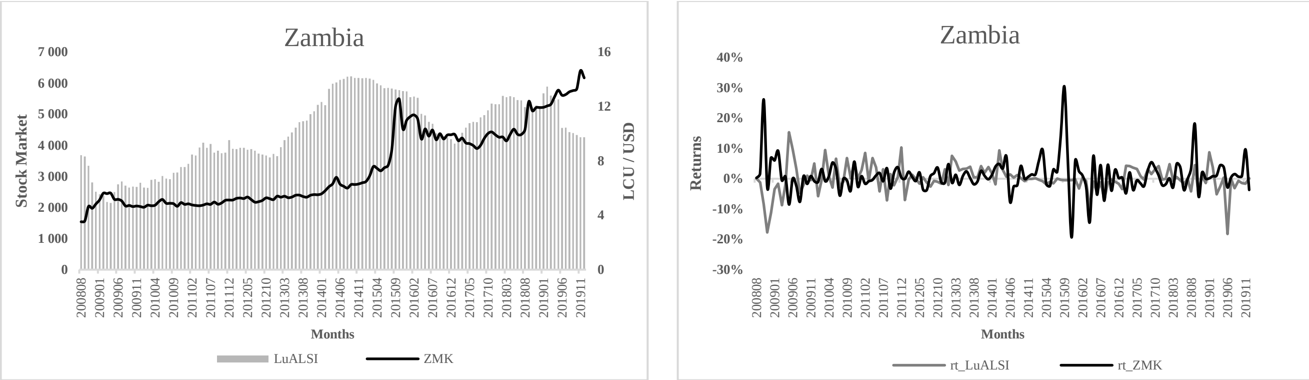

Figure 4.12: Zambia Stock and Currency Markets

Data source: IMF International Statistics and Iress

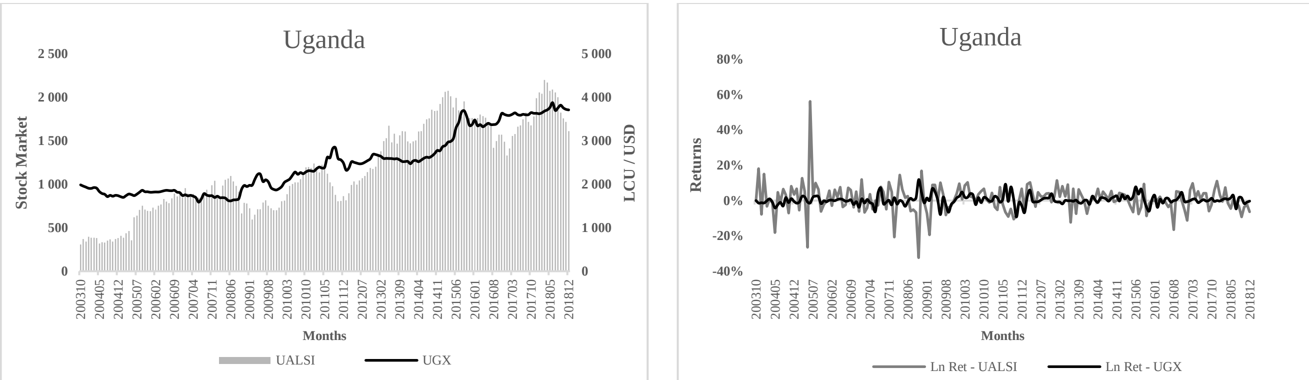

Figure 4.13: Uganda Stock and Currency Markets

Data source: IMF International Statistics, Kenya's Capital Market Authority and Iress

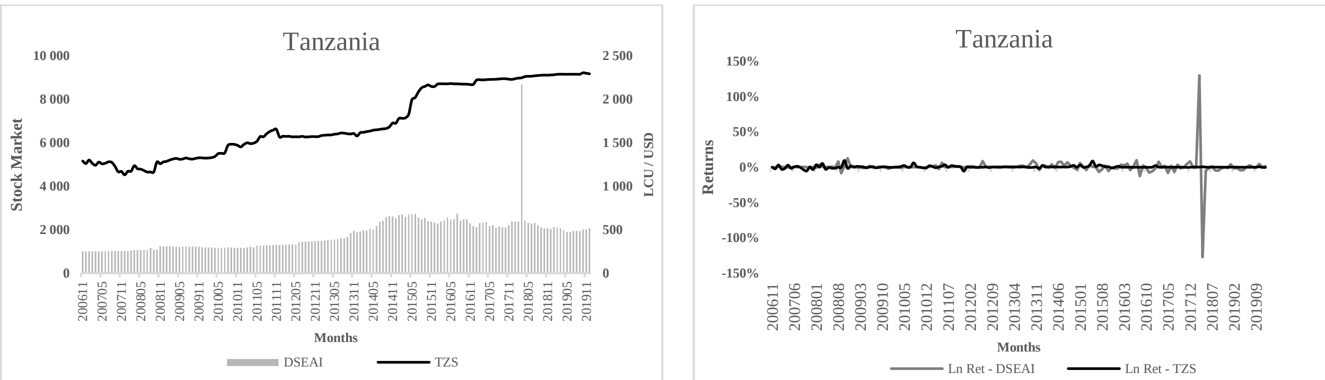

Figure 4.14: Tanzania Stock and Currency Markets

Data source: IMF International Statistics, Kenya's Capital Market Authority and Iress

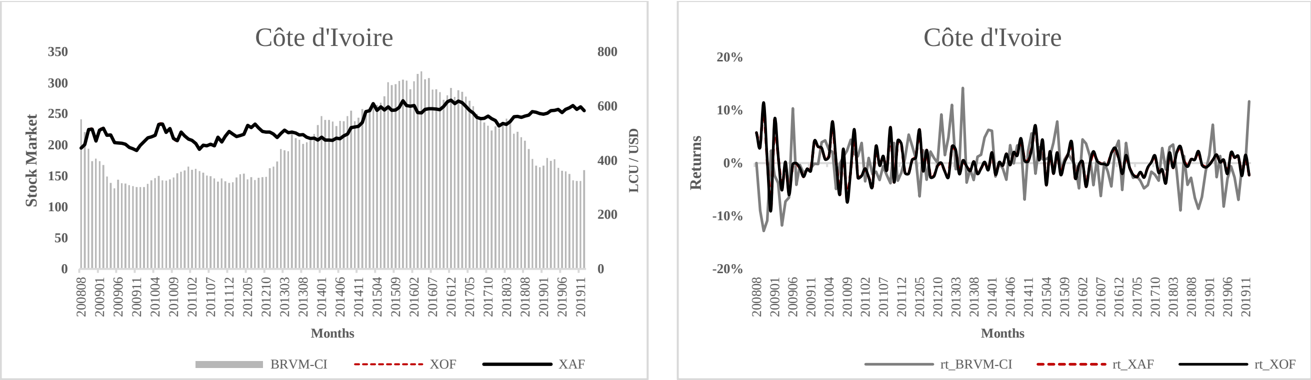

Figure 4.15: Côte d'Ivoire Stock and Currency Markets

Data source: IMF International Statistics and Iress

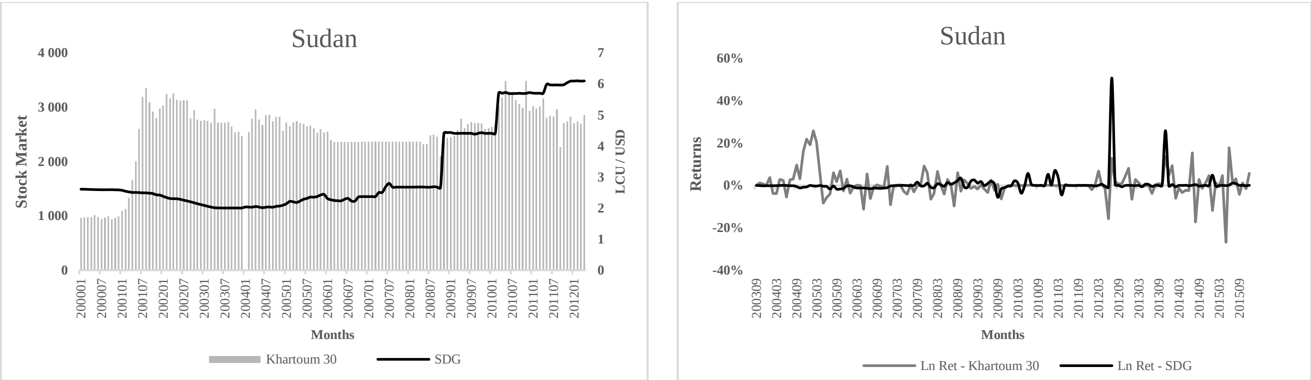

Figure 4.16: Stock and Currency Markets[4]

Data source: IMF International Statistics and Sanabelfs Securities[5]

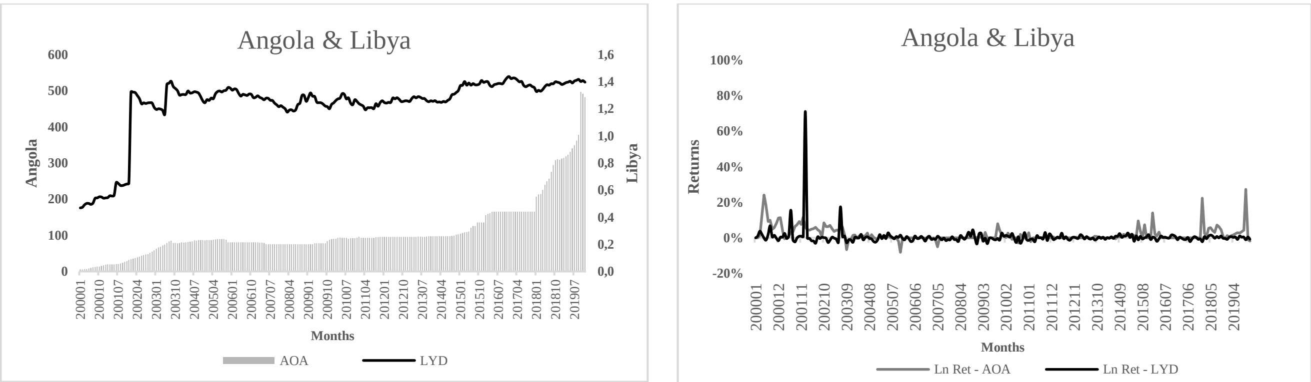

Figure 4.17: Angola and Libya Currency Markets

Data source: IMF International Statistics

[4] Due to data availability, this dataset is up to end of 2015/12.
[5] http://www.sanabelfs.com/arabic/Page.aspx?pid=40&lang=en

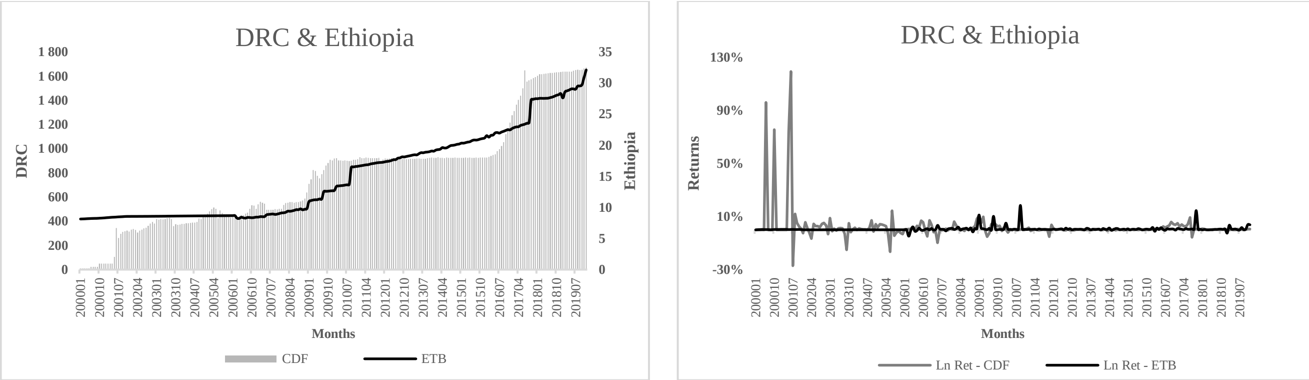

Figure 4.18: DRC and Ethiopia Currency Markets

Data source: IMF International Statistics

4.2 Empirical Data Analysis

4.2.1 Introduction

This sub-chapter responds to the questions hypothesised in subsection 1.5 and will use using statistical frameworks discussed in Chapter 3 and empirical data introduced in section 4.1. The overall data analysis and discussions aim to give insights on an intra-economy level and assumes that data returns being analysed are weakly stationary and this concern is tested in section 4.2.3. Sections 4.2.2 and 4.2.3 discuss the relationship that exists on a returns level using results from tests on the normality assumption, linear correlation, autocorrelation and stationarity. Each relationship offers guidance on which and how volatility models are applied in later sections and give some pre-expectations of the results and outcomes. Table 4.3 shows basic statistics of the sampled univariates offers a view on the data's degree of asymmetry using skewness; excess kurtosis and p-value results from two normality tests i.e. Jarque-Bera (JB) and Shapiro-Wilks (SW).

Table 4.3 Descriptive Statistics of Sampled Variables' Returns

Variable	Basic Statistic							JB	SW
	#Obs.	Min	Mean	Max	St. dev	Skewness	Kurtosis	*(p- values of test)*	
Gold	240	-19.10%	0.70%	13.03%	4.82%	-34.14%	1.14	0.02%	1.34%
Oil	240	-31.72%	0.38%	18.43%	8.51%	-102.27%	1.62	0.00%	0.00%
SALSI	240	-15.03%	0.81%	13.13%	4.64%	-24.36%	0.63	4.27%	6.11%
ZAR	240	-11.48%	0.33%	20.09%	4.83%	57.48%	0.95	0.00%	0.25%
NSE	240	-36.59%	0.64%	32.35%	6.86%	-38.38%	5.16	0.00%	0.00%
NGN	240	-5.32%	0.54%	35.26%	3.12%	661.75%	65.15	0.00%	0.00%
BSEDCI	240	-10.70%	0.70%	13.85%	3.27%	28.69%	2.83	0.00%	0.00%
BWP	240	-7.99%	0.34%	19.13%	3.26%	113.53%	5.19	0.00%	0.00%
KNSE	240	-25.67%	0.04%	15.98%	5.89%	-70.52%	2.89	0.00%	0.00%
KES	240	-10.63%	0.14%	11.84%	2.06%	15.25%	9.47	0.00%	0.00%
EGX 30	240	-40.33%	1.00%	31.19%	9.11%	-16.37%	1.91	0.00%	0.15%
EGP	240	-17.19%	0.64%	69.60%	5.07%	1062.79%	142.57	0.00%	0.00%
GSE	240	-32.37%	1.28%	20.11%	5.75%	-45.45%	5.87	0.00%	0.00%
GHS	240	-22.53%	1.14%	15.79%	2.84%	-103.01%	23.26	0.00%	0.00%
Tunindex	240	-11.78%	0.70%	12.63%	3.46%	-6.10%	1.42	0.00%	0.12%
TND	240	-5.50%	0.32%	9.54%	2.16%	46.63%	1.54	0.00%	0.17%
DZAIR	144	-7.77%	0.30%	13.65%	2.53%	97.17%	5.79	0.00%	0.00%
DZD	144	-2.91%	0.41%	9.88%	1.69%	228.49%	8.54	0.00%	0.00%
MASI	216	-16.97%	0.58%	18.34%	4.18%	14.18%	2.73	0.00%	0.00%
MAD	216	-6.99%	-0.09%	9.78%	2.25%	46.53%	2.28	0.00%	0.00%
XOF	137	-8.94%	0.24%	11.44%	2.98%	42.78%	1.74	0.00%	0.33%
BRVM-CI	137	-12.82%	-0.30%	14.20%	4.50%	13.36%	0.87	9.30%	19.15%
ZMK	137	-19.37%	1.02%	30.40%	5.55%	150.12%	9.08	0.00%	0.00%
LuALSI	137	-18.23%	0.11%	15.32%	4.54%	-54.35%	3.57	0.00%	0.00%
UGX	132	-9.26%	0.61%	11.89%	2.89%	23.52%	3.29	0.00%	0.00%
UALSI	132	-32.34%	0.42%	16.77%	6.62%	-111.09%	3.89	0.00%	0.00%
TZS	158	-5.54%	0.36%	9.55%	1.74%	152.33%	9.32	0.00%	0.00%
DSEAI	158	-127.27%	0.46%	129.85%	14.92%	15.99%	67.78	0.00%	0.00%
ETB	240	-4.81%	0.57%	18.41%	1.92%	622.12%	47.35	0.00%	0.00%
CDF	240	-27.10%	2.18%	119.38%	12.39%	695.87%	54.45	0.00%	0.00%
LYD	240	-3.45%	0.45%	71.15%	5.01%	1202.46%	164.00	0.00%	0.00%
AOA	240	-8.15%	1.84%	27.29%	4.08%	294.17%	12.59	0.00%	0.00%
SDG	147	-5.58%	0.58%	50.70%	4.90%	832.33%	77.71	0.00%	0.00%
Khartoum 30	147	-26.78%	0.70%	25.83%	6.54%	46.66%	4.51	0.00%	0.00%

4.2.2 Linear and Rank Correlation

This section is an initial step towards assessing whether there is an association amongst sampled variables from a price returns' perspective per economy. The linear association between specified variables' return series is shown from Table 4.4 up to Table 4.22. The tables initially show static or unconditional Pearson and Kendall correlation coefficients and their two correlation tests on a bivariate return level. The correlation tests are both based on the null hypothesis of having each association measure being zero between variables. Both correlation tests have shortcomings as a value of zero for either of the association measures does not translate to independence between variables. Figure 4.19 to Figure 4.37, represent 12 months rolling window of correlation per country. The figures also show that a constant correlation assumption cannot be a realistic view of the relation amongst variables in any economy as the visuals show over time alternating levels of bivariate association.

From a return perspective, there are cases where sample association measures give a similar and alternating perception of dependence and correlation, such as the association between LuALSI, DZD and Crude oil. There are also cases where the sign indicating the type of association are not the same such as the values for EGX30 index and EGP, clear showing the difference of what is quantified by each measure. Gold, apart from economies such as Tanzania, Nigeria and DRC, is inversely related to all currencies as all show a consistent negative correlation and tau and with gold throughout the sampled period. Currencies and, where they exist, stock markets of countries such as Nigeria, Sudan, Libya , Egypt, Algeria and Angola would be expected to have relatively high levels of association with crude oil as the commodity is a primary exported good that also feeds significantly into the top 75% of goods these countries export. In the ensuing subchapters association is modelled from a volatility perspective. To model volatility, data used must have a level of stationarity; and lag-value influence in the form of autocorrelation, must also be incorporated hence the test for serial dependence and its modelling in section 4.2.3.

Table 4.4: Unconditional Correlation between Crude Oil and Gold Returns

Variables	***ρ***	***ρ_τ***	***p*-val (ρ)**	***p*-val (ρ_τ)**
Gold and Oil	11%	8%	9%	6%

Figure 4.19: Rolling Correlation between Crude Oil and Gold Returns

Table 4.5: Unconditional Correlation amongst Variables of South Africa

Economy	**Variables**	***ρ***	***ρ_τ***	***p*-val (ρ)**	***p*-val (ρ_τ)**
	SALSI and ZAR	-10.6%	-9.7%	10.1%	2.5%
	SALSI and Gold	20.7%	12.0%	0.1%	0.6%
South Africa	SALSI and Oil	18.9%	11.5%	0.3%	0.8%
	ZAR and Gold	-28.8%	-17.0%	0.0%	0.0%
	ZAR and Oil	-19.8%	-13.6%	0.2%	0.2%

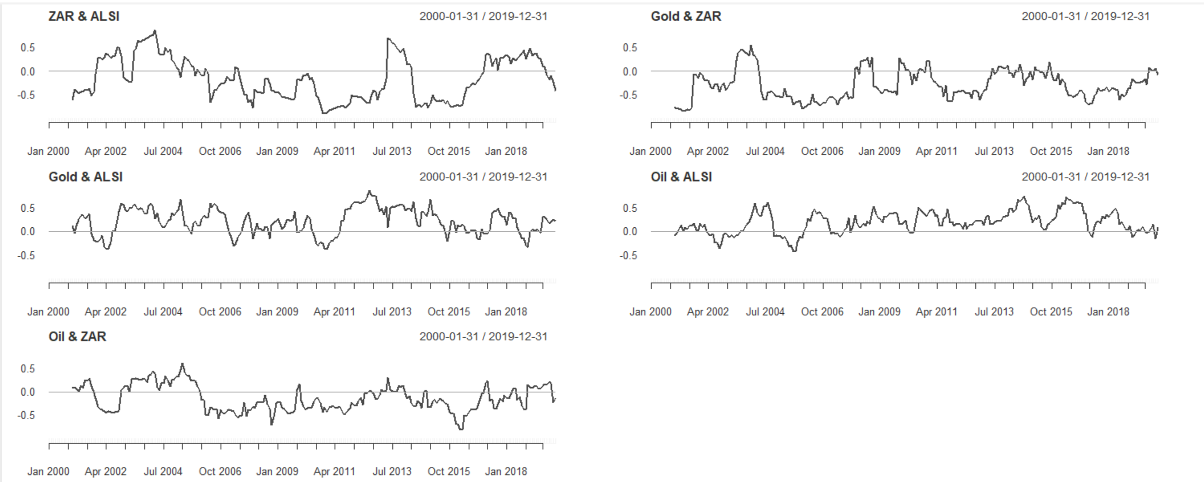

Figure 4.20: Rolling Correlation amongst Variables of South Africa

Table 4.6: Unconditional Correlation amongst Botswana Variables

Economy	**Variables**	ρ	ρ_τ	***p*-val (ρ)**	***p*-val (ρ_τ)**
	BSEDCI and BWP	14.5%	8.1%	2.5%	6.3%
	BSEDCI and Gold	-4.7%	-4.6%	46.9%	28.7%
Botswana	BSEDCI and Oil	-0.3%	-5.2%	96.2%	22.9%
	BWP and Gold	-30.4%	-17.4%	0.0%	0.0%
	BWP and Oil	-21.3%	-15.5%	0.1%	0.0%

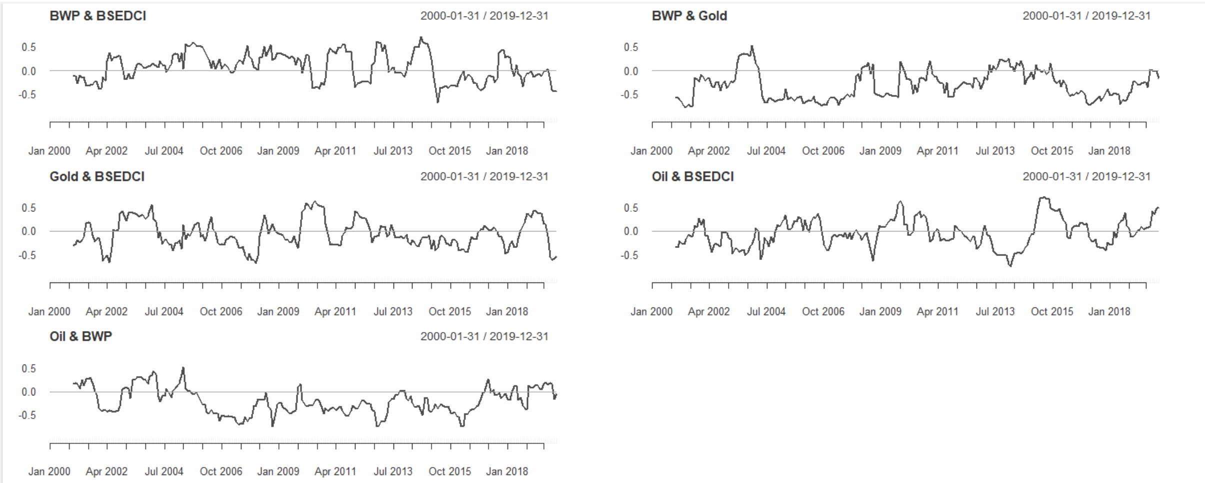

Figure 4.21: Rolling Correlation amongst Variables of Botswana

Table 4.7: Unconditional Correlation amongst Nigeria Variables

Economy	**Variables**	ρ	ρ_τ	***p*-val (ρ)**	***p*-val (ρ_τ)**
	NSE and NGN	-6.5%	-5.6%	31.5%	19.7%
	NSE and Gold	3.4%	-4.1%	60.5%	34.7%
Nigeria	NSE and Oil	21.3%	10.3%	0.1%	1.8%
	NGN and Gold	7.4%	0.6%	25.7%	88.8%
	NGN and Oil	-13.3%	-4.8%	4.0%	26.9%

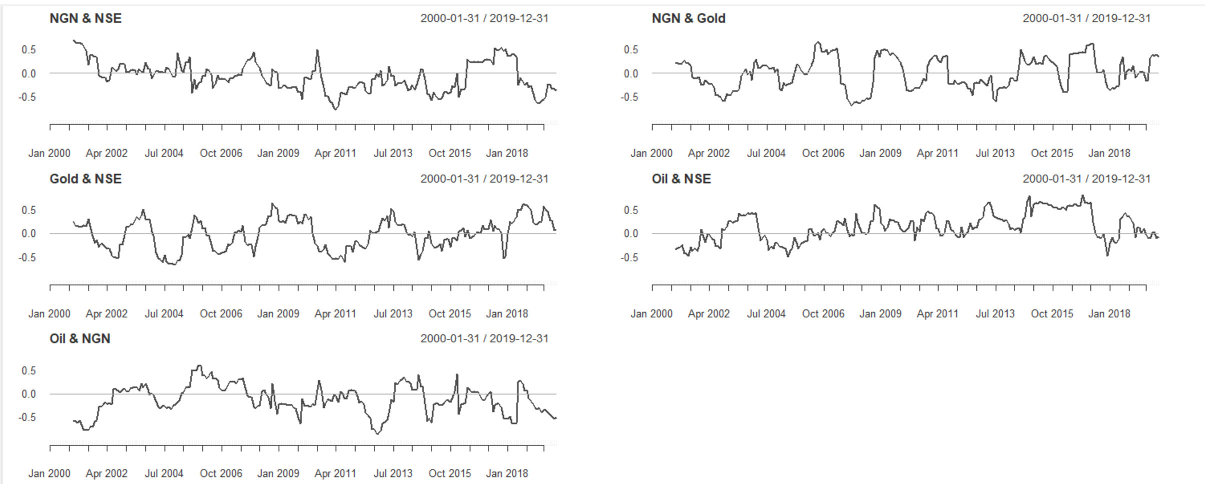

Figure 4.22: Rolling Correlation amongst Variables of Nigeria

Table 4.8: Unconditional Correlation amongst Kenya Variables

Economy	Variables	ρ	ρ_τ	p-val (ρ)	p-val (ρ_τ)
	NSE and KES	-12.9%	-4.9%	4.6%	25.4%
	NSE and Gold	0.5%	3.1%	94.3%	46.8%
Kenya	NSE and Oil	-3.4%	-4.2%	59.7%	32.8%
	KES and Gold	-5.0%	-4.3%	43.8%	32.6%
	KES and Oil	-13.0%	-6.8%	4.5%	11.6%

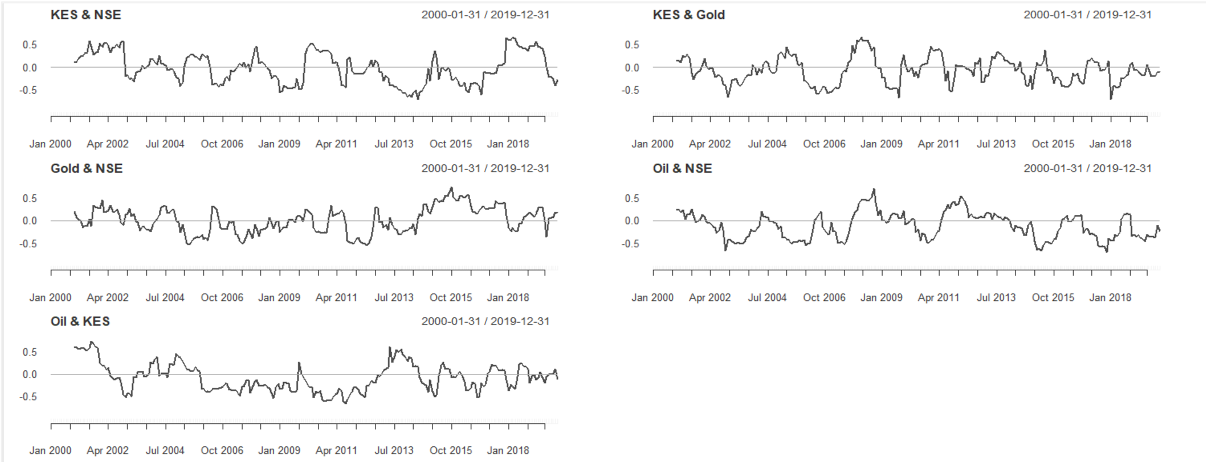

Figure 4.23: Rolling Correlation amongst Variables of Kenya

Table 4.9: Unconditional Correlation amongst Egypt Variables

Economy	Variables	ρ	ρ_τ	p-val (ρ)	p-val (ρ_τ)
	EGX 30 and EGP	24.0%	-6.2%	0.0%	15.6%
	EGX 30 and Gold	18.6%	8.7%	0.4%	4.6%
Egypt	EGX 30 and Oil	22.3%	10.9%	0.0%	1.2%
	EGP and Gold	-11.9%	-10.0%	6.5%	2.2%
	EGP and Oil	-5.6%	-0.5%	39.0%	90.6%

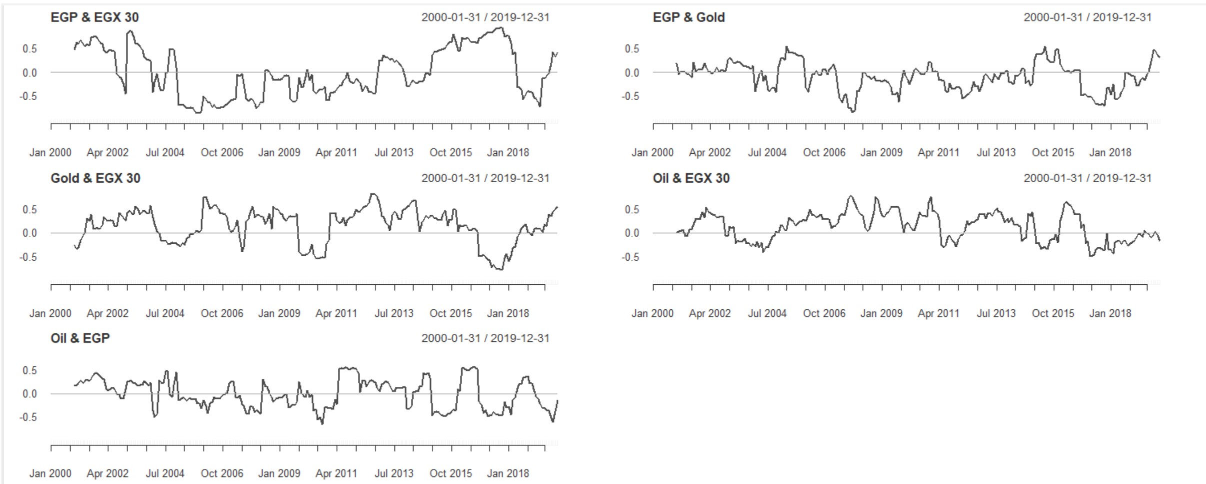

Figure 4.24: Rolling Correlation amongst Variables of Arab Republic of Egypt

Table 4.10: Unconditional Correlation amongst Ghana Variables

Economy	**Variables**	ρ	ρ_τ	p-val (ρ)	p-val (ρ_τ)
	GSE and GHS	-4.5%	-0.1%	48.6%	97.3%
	GSE and Gold	1.0%	0.5%	87.8%	91.7%
Ghana	GSE and Oil	0.8%	4.9%	89.8%	26.1%
	GHS and Gold	-9.6%	-10.1%	13.9%	1.9%
	GHS and Oil	5.0%	-3.0%	44.1%	48.2%

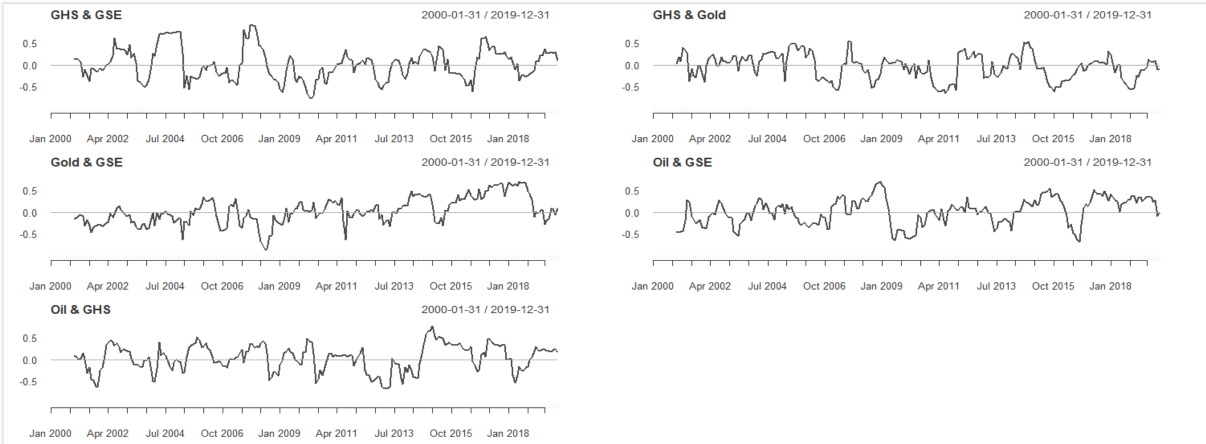

Figure 4.25: Rolling Correlation amongst Variables of Ghana

Table 4.11: Unconditional Correlation amongst Tunisia Variables

Economy	**Variables**	ρ	ρ_τ	p-val (ρ)	p-val (ρ_τ)
	Tunindex and TND	1.6%	2.1%	80.5%	63.0%
	Tunindex and Gold	1.9%	1.8%	76.6%	67.0%
Tunisia	Tunindex and Oil	1.2%	2.5%	85.1%	56.2%
	TND and Gold	-38.3%	-26.1%	0.0%	0.0%
	TND and Oil	-15.2%	-12.4%	1.8%	0.4%

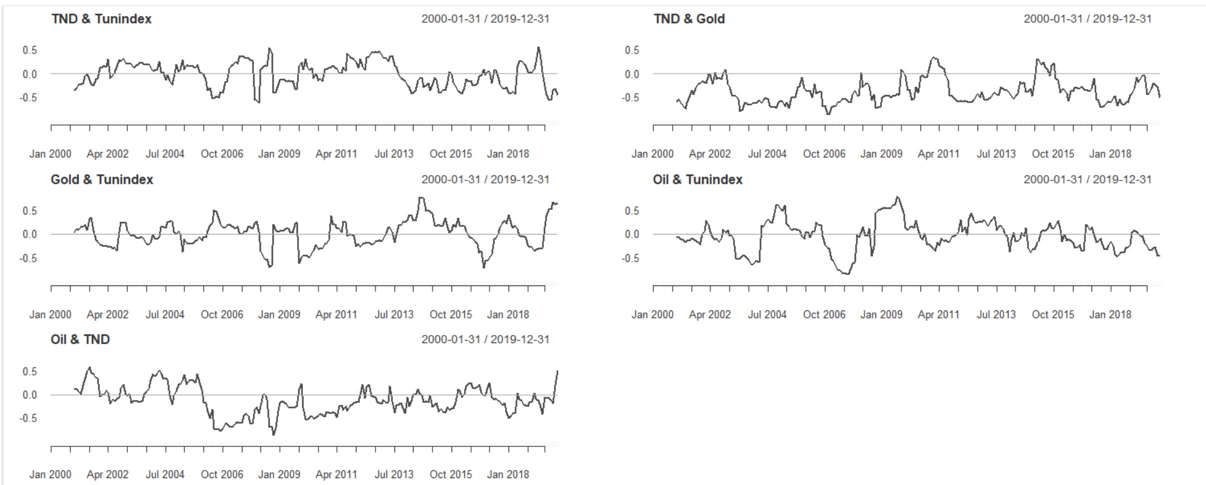

Figure 4.26: Rolling Correlation amongst Variables of Tunisia

Table 4.12: Unconditional Correlation amongst Algeria Variables

Economy	**Variables**	ρ	ρ_τ	p**-val (ρ)**	p**-val (ρ_τ)**
	DZAIR and DZD	4.7%	4.5%	57.8%	43.6%
	DZAIR and Gold	-8.0%	-2.5%	34.3%	66.5%
Algeria	DZAIR and Oil	5.6%	-1.3%	50.7%	81.5%
	DZD and Gold	-19.4%	-9.4%	2.0%	9.5%
	DZD and Oil	-29.3%	-8.9%	0.0%	11.4%

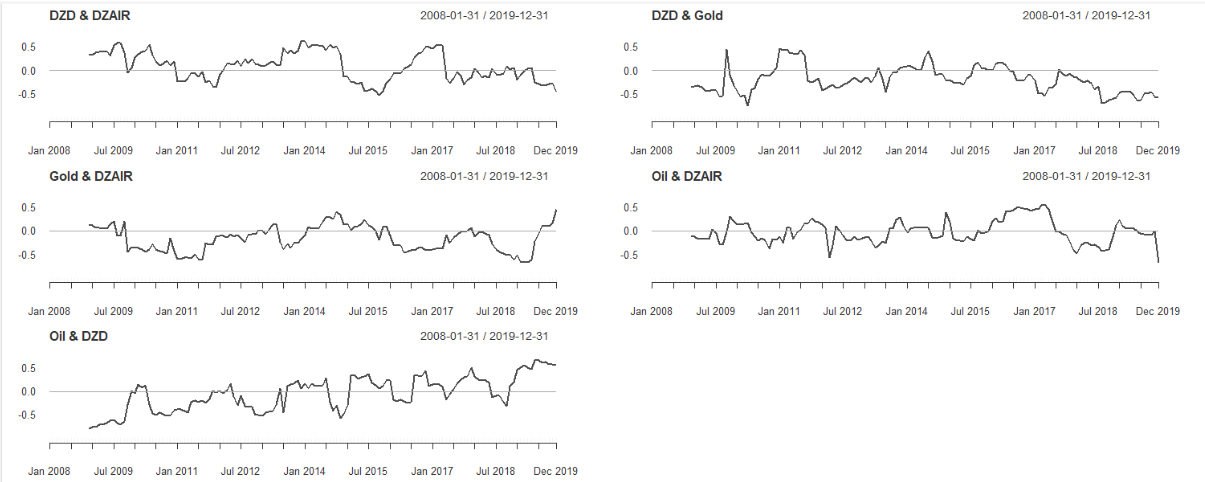

Figure 4.27: Rolling Correlation amongst Variables of Algeria

Table 4.13: Unconditional Correlation amongst Morocco Variables

Economy	**Variables**	ρ	ρ_τ	p**-val (ρ)**	p**-val (ρ_τ)**
	MASI and MAD	-4.0%	-1.1%	56.0%	80.2%
	MASI and Gold	4.8%	1.3%	48.6%	77.5%
Morocco	MASI and Oil	5.5%	1.7%	41.8%	71.2%
	MAD and Gold	-37.8%	-24.1%	0.0%	0.0%
	MAD and Oil	-20.8%	-12.8%	0.2%	0.5%

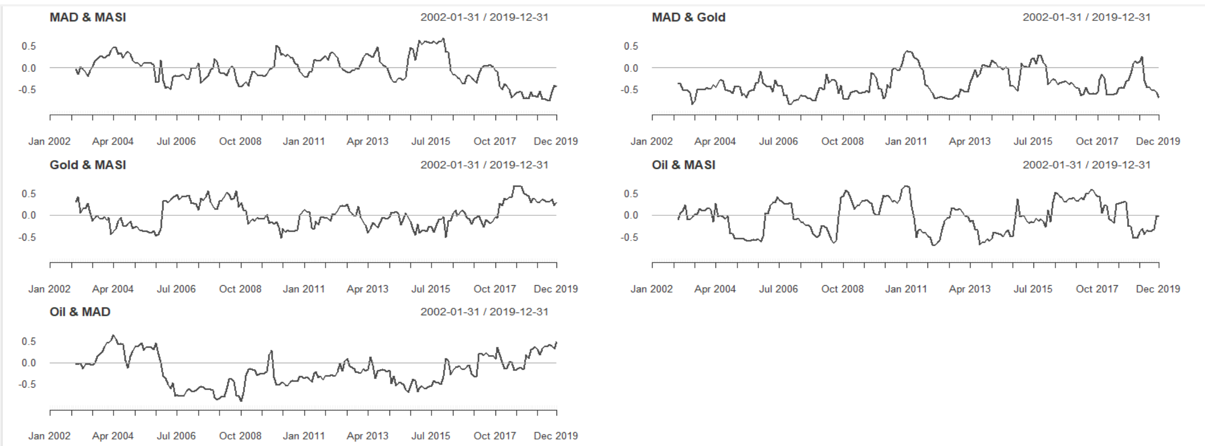

Figure 4.28: Rolling Correlation amongst Variables of Morocco

Table 4.14: Unconditional Correlation amongst Côte d'Ivoire Variables

Economy	**Variables**	ρ	ρ_τ	***p*-val (ρ)**	***p*-val (ρ_τ)**
	BRVM-CI and XOF	-10.7%	-4.4%	21.4%	45.0%
	BRVM-CI and Gold	-1.4%	-4.0%	86.8%	49.1%
Côte d'Ivoire	BRVM-CI and Oil	19.2%	6.6%	2.5%	25.5%
	XOF and Gold	-34.5%	-19.8%	0.0%	0.1%
	XOF and Oil	-22.6%	-12.6%	0.8%	2.9%

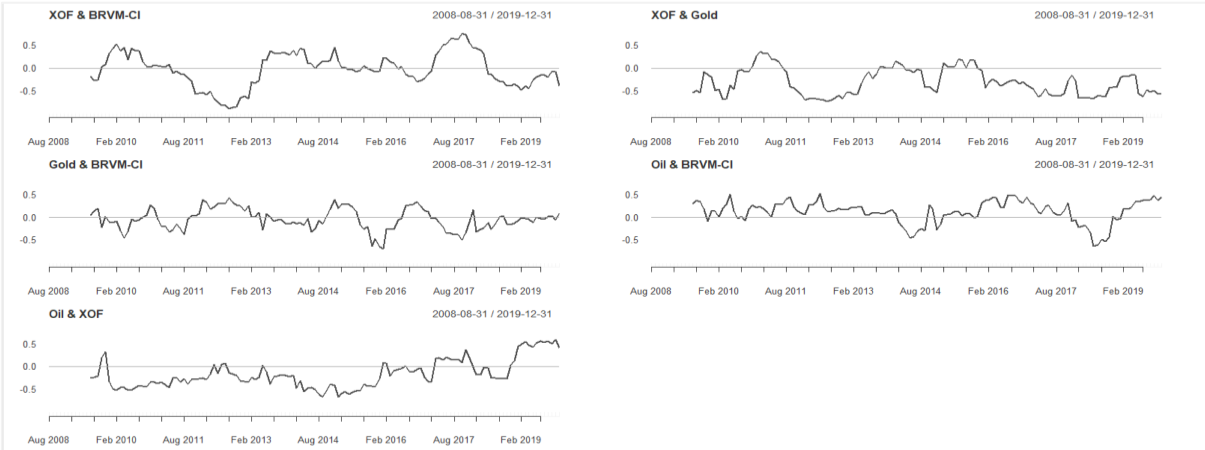

Figure 4.29: Rolling Correlation amongst Variables of Côte d’Ivoire

Table 4.15: Unconditional Correlation amongst Zambia Variables

Economy	**Variables**	ρ	ρ_τ	***p*-val (ρ)**	***p*-val (ρ_τ)**
	LuALSI and ZMK	-2.3%	-3.8%	79.1%	51.2%
	LuALSI and Gold	-16.1%	-9.5%	6.0%	9.9%
Zambia	LuALSI and Oil	30.4%	5.8%	0.0%	31.5%
	ZMK and Gold	-17.2%	-7.1%	4.5%	21.8%
	ZMK and Oil	-21.4%	-12.6%	1.2%	2.9%

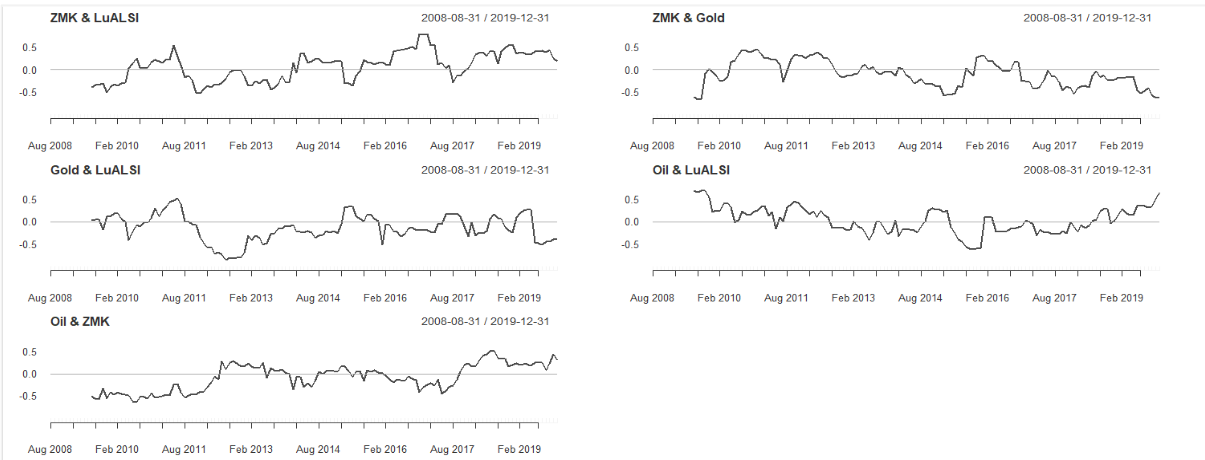

Figure 4.30: Rolling Correlation amongst Variables of Zambia

Table 4.16: Unconditional Correlation amongst Tanzania Variables

Economy	**Variables**	ρ	ρ_τ	p**-val (ρ)**	p**-val (ρ_τ)**
	DSEAI and TZS	-1.4%	1.1%	86.2%	83.2%
	DSEAI and Gold	3.4%	5.1%	67.4%	34.3%
Tanzania	DSEAI and Oil	0.0%	5.3%	99.5%	32.2%
	TZS and Gold	-6.0%	2.3%	45.5%	66.4%
	TZS and Oil	-10.2%	14.2%	20.2%	0.8%

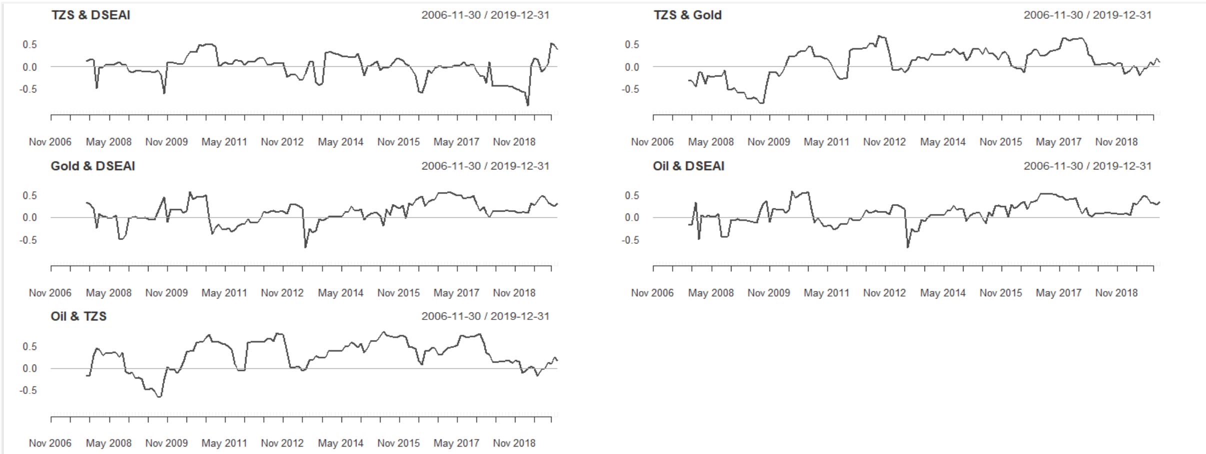

Figure 4.31: Rolling Correlation amongst Variables of Tanzania

Table 4.17: Unconditional Correlation amongst Uganda Variables

Economy	**Variables**	ρ	ρ_τ	p**-val (ρ)**	p**-val (ρ_τ)**
	UALSI and UGX	-3.4%	7.6%	70.0%	11.7%
	UALSI and Gold	12.2%	-1.5%	16.3%	75.9%
Uganda	UALSI and Oil	15.3%	6.7%	7.9%	16.8%
	UGX and Gold	-16.2%	-4.9%	6.4%	32.0%
	UGX and Oil	-23.3%	-8.5%	0.7%	8.0%

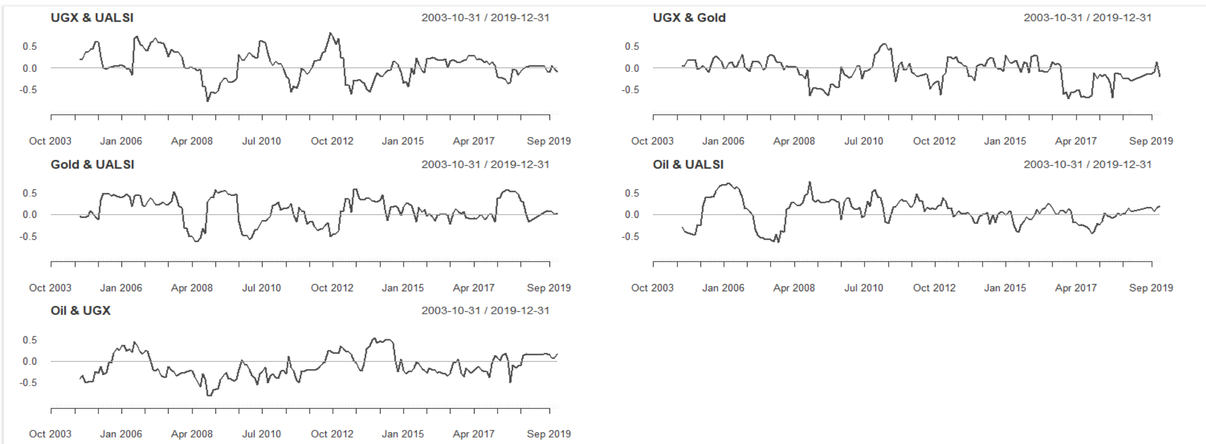

Figure 4.32: Rolling Correlation amongst Variables of Uganda

Table 4.18: Unconditional Correlation amongst Sudan Variables

Economy	**Variables**	ρ	ρ_τ	p**-val (ρ)**	p**-val (ρ_τ)**
Sudan	Khartoum 30 and SDG	19.1%	6.4%	2.0%	25.0%
	Khartoum 30 and Gold	-9.1%	-7.8%	27.5%	15.9%
	Khartoum 30 and Oil	6.2%	2.0%	45.8%	72.0%
	SDG and Gold	-6.1%	-10.8%	46.2%	5.2%
	SDG and Oil	1.7%	-0.1%	83.6%	98.7%

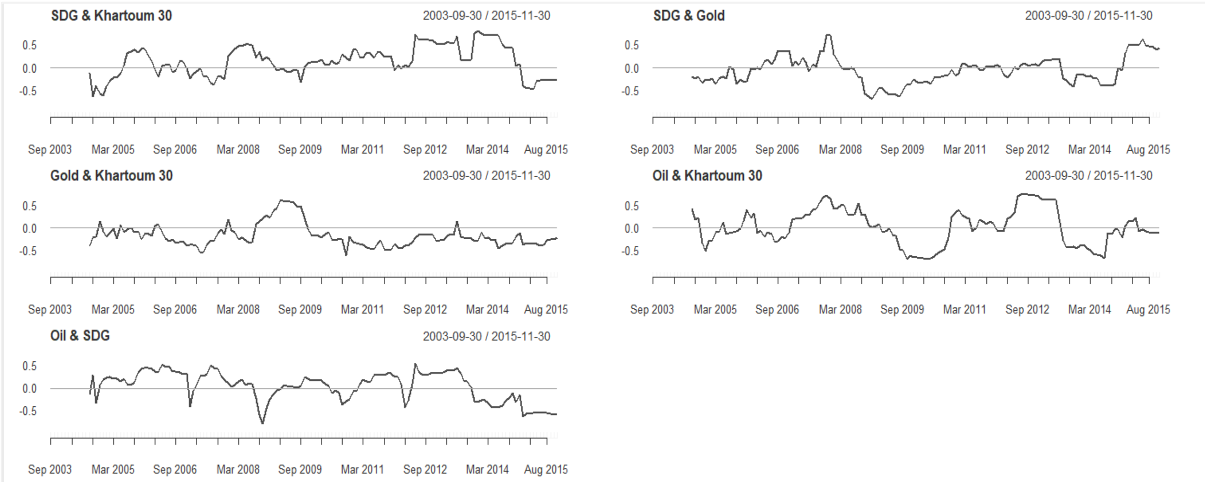

Figure 4.33: Rolling Correlation amongst Variables of Sudan

Table 4.19: Unconditional Correlation amongst Libya Variables

Economy	**Variables**	ρ	ρ_τ	p**-val (ρ)**	p**-val (ρ_τ)**
Libya	LYD and Gold	-11.3%	-29.2%	8.1%	0.0%
	LYD and Oil	-2.7%	-14.7%	67.5%	0.1%

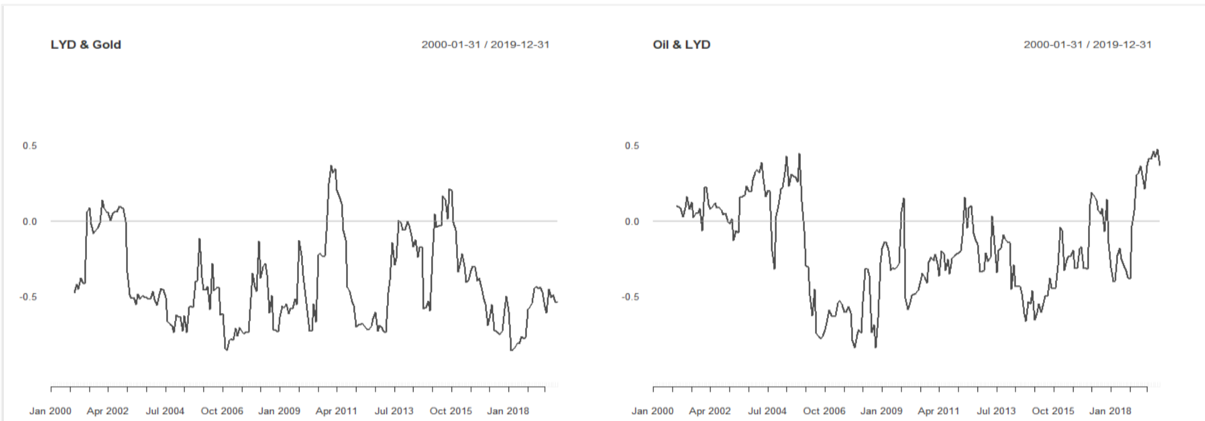

Figure 4.34: Rolling Correlation amongst Variables of Libya

Table 4.20: Unconditional Correlation amongst Angola Variables

Economy	Variables	ρ	ρ_τ	p-val (ρ)	p-val (ρ_τ)
Angola	AOA and Gold	-0.9%	-7.0%	89.5%	10.6%
	AOA and Oil	-0.6%	-0.1%	92.4%	97.9%

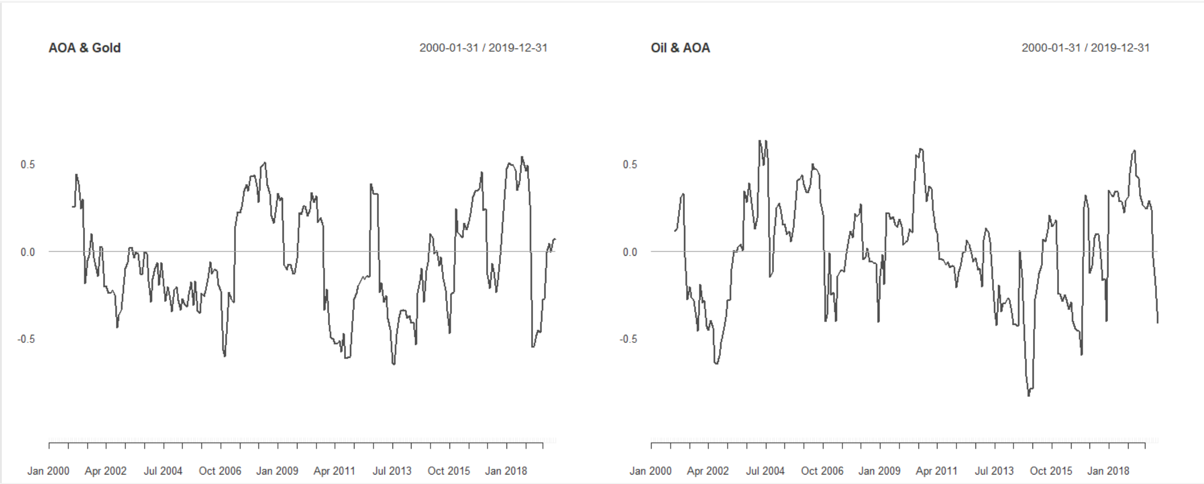

Figure 4.35: Rolling Correlation amongst Variables of Angola

Table 4.21: Unconditional Correlation amongst DR. Congo Variables

Economy	Variables	ρ	ρ_τ	p-val (ρ)	p-val (ρ_τ)
DRC	CDF and Gold	2.6%	4.3%	69.1%	32.7%
	CDF and Oil	2.2%	0.9%	73.0%	83.2%

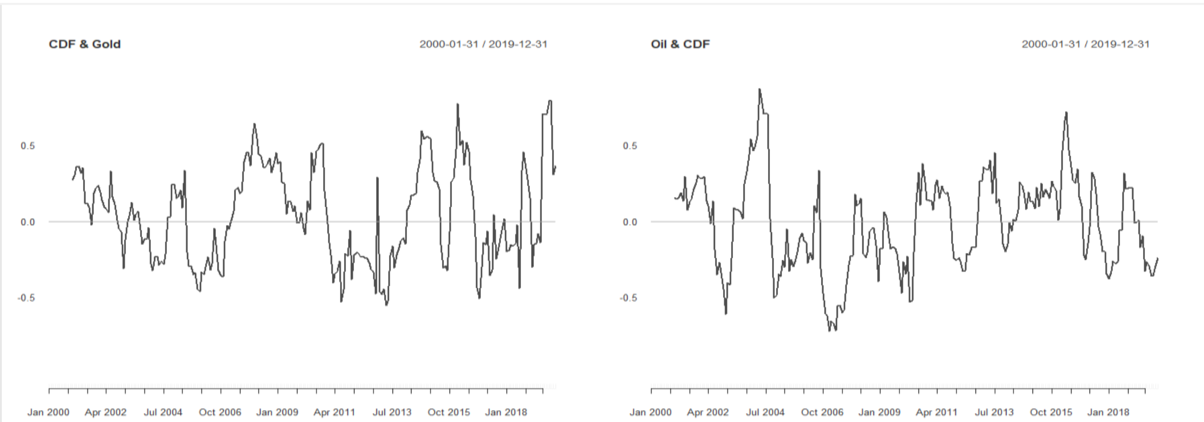

Figure 4.36: Rolling Correlation amongst Variables of DR. Congo

Table 4.22: Unconditional Correlation amongst Ethiopian Variables

Economy	**Variables**	***ρ***	***ρ_τ***	***p*-val (ρ)**	***p*-val (ρ_τ)**
Ethiopia	ETB and Gold	4.5%	-1.0%	49.2%	81.7%
	ETB and Oil	5.7%	-2.9%	37.9%	50.7%

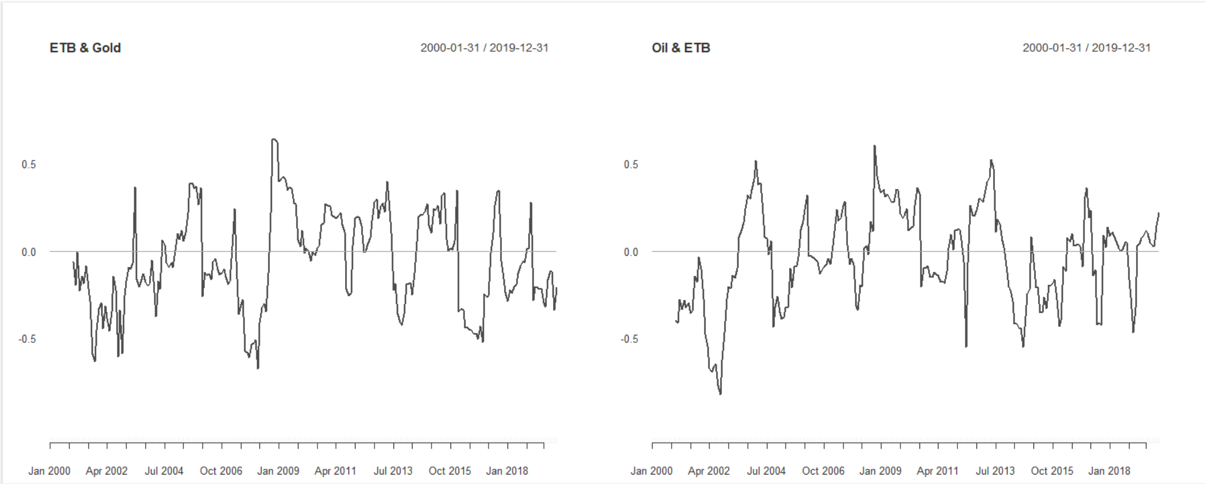

Figure 4.37: Rolling Correlation amongst Variables of Ethiopia

4.2.3 Serial Correlation and Stationarity

This subtopic deals with the possible presence of autocorrelation or lag (k) correlation between the return at time t, r_t, and its past forms $\{r_{t-1}, r_{t-2}, \ldots r_{t-k}\}$. A visual of the autocorrelation in the sampled data is shown in the figures in Chapter 1Appendix A. using the sample autocorrelation (ACF) and partial autocorrelation (PACF) functions of each sampled variable's residuals. The results of the Ljung–Box test for the existence of autocorrelation between lag (k) returns are also reported in Table 4.23 and are based on 5 lags per univariate. The results of the ADF, KPSS and ZA tests presented in Table 4.23 are based on a 5% level of significance (5% LoS) and suggest that most of the data is stationary with the exception of the TZS and AOA. The stationary results are tested for the first 10 lags of each sampled univariate, except for Algeria's DZD and DZAIR and Zambia's LuALSI which were tested at 8 lags and Côte d'Ivoire's BRVM which was tested at 9 lags. The AOA and TZS are both stationary when the test is performed at 6 lags with resulting *p*-values of 0.03805 and 0.0155, respectively from the ADF test. The ZA test allows for one structural break point in the data and shows results of most univariates being stationary given the break in both the trend and growth. The ZA test applied uses as critical values -5.57, -5.08 and -4.82 and these are based respectively on 1%, 5% and 10% level of significance. The Ljung-box test suggests that there are variables that have serial correlation because when applying the test at a 5% LoS, variables such as crude oil; Ghana's cedi and Nigeria's naira fail to reject the null of no significant autocorrelation and that there is a need to consider past returns when analysing future returns from these variables. Other variables that suggest existence of serial correlation are in bold figures under the "Ljung-box" column of Table 4.23 and suggest that an ARMA-type of model would be appropriate.

Table 4.23 Results from Ljung–Box, ADF, KPSS and ZA Tests

Variable	**Ljung–Box**	**ADF**	**KPSS**	**ZA**
	(p - value of test)			
Gold	42.19%	1%	10%	-5.88
Oil	**0.05%**	1%	10%	-5.16
SALSI	43.61%	1%	10%	-5.40
ZAR	87.30%	1%	10%	-4.87
NSE	**0.04%**	1%	10%	-4.74
NGN	7.85%	1%	10%	-7.58
BSEDCI	**0.00%**	1%	7%	-5.12
BWP	50.37%	1%	10%	-5.44
NSE	**0.30%**	1%	10%	-5.37
KES	1.09%	1%	10%	-7.41
EGX 30	**0.04%**	1%	10%	-5.70
EGP	**0.88%**	1%	10%	-7.83
GSE	83.70%	1%	10%	-5.47
GHS	**0.00%**	1%	10%	-5.81
Tunindex	21.07%	1%	10%	-5.98
TND	32.41%	1%	9%	-6.31
DZAIR	16.28%	3%	10%	-5.06
DZD	1.38%	1%	10%	-5.80
MASI	4.81%	3%	10%	-5.12
MAD	52.65%	1%	7%	-5.39
XOF	66.98%	1%	10%	-4.48
BRVM-CI	6.42%	1%	10%	-4.97
ZMK	82.52%	1%	10%	-5.66
LuALSI	**0.81%**	1%	10%	-5.81
UGX	7.04%	1%	10%	-6.28
UALSI	22.92%	1%	10%	-5.34
TZS	40.09%	5.5%	10%	-4.88
DSEAI	**0.00%**	1%	10%	-5.50
ETB	99.99%	2%	8%	-5.07
CDF	2.47%	2%	5%	-11.04
LYD	90.26%	1%	9%	-10.27
AOA	**0.00%**	6%	8%	-5.54
SDG	99.99%	1%	5%	-7.92
Khartoum 30	**0.66%**	4.6%	10%	-5.70

4.3 Empirical Modelling, Results and Discussion

4.3.1 Introduction

This section presents a discussion on the results of modelling conditional dependence of variables intra-economy. The full maximum likelihood method (ML) and inference functions for margins (IMF) are some of the various modelling approaches that are available in literature used for the estimation of the conditional dependence metrics. The ML and IMF procedures computationally differ in a sense that the ML method estimates jointly all parameters by simultaneously maximising the joint likelihood with respect to each of the parameters in the copula and marginal structure. The IMF method, which is computationally convenient and applied in this study, is a multistep (generally two steps) procedure that requires an initial estimation of the marginals and using a probability integral transformed (PIT) version of the initially derived parameters as inputs to derive the dependence parameters (Durrleman, Nikeghbali and Roncalli, 2000; Bauwens, Hafner and Laurent, 2012). The PIT transformation process of section 3.3.1 is required because to derive the dependence parameter in the second step, uniform (Unif (0,1)) distributed inputs are a requirement. The transformation is performed either parametrically on the standardised residuals of the fitted margin models or semi-parametrically in the empirical distribution function. In the following section, a step-wise approach or IMF method is put to use by initially estimating the univariate marginals and extracting their standardised residuals in order to provide a view on the multivariate joint structure per economy .The estimation process uses R’s rugarch and rmgarch packages of Ghalanos (2013).

4.3.2 Modelling of Univariate Margins

This subtopic deals with modelling the univariate margins of each sampled variable. The copula based MGARCH approach to modelling volatility, relates a univariate to a MGARCH process and a copula. From Sklar’s theorem, univariate margins from varying distributions can be used in conjunction with a copula to describe a joint distribution function that describes the dependence and correlation separately. The data has been tested and shown to have serial dependence in the correlograms presented in Chapter 1Appendix B.

Due to the presence of serial dependence, an ARMA(p_1, q_1)-GARCH(p_2, q_2) model with either a Gaussian (*N*), skewed-Gaussian (s*N*), skewed Student-t (s*t*) or Student t (*t*) distributed innovations ($\boldsymbol{Z_t}$) are chosen for the marginals. Various GARCH models are compared with the standard GARCH model and chosen (with suitable real values of p_1, q_1, p_2, q_2) based on the minimum Akaike (and Schwarz–Bayesian) information criterion, diagnostics such as the behaviour of standardised residuals and the model's ability to deal with volatility clustering that is tested by an ARCH test. The selected models, their likelihood (LLH), information criteria values (only AIC) and *p*-values of the goodness of fit are reported in Table 4.24 and Table 4.25, respectively. Parameter estimates of each fitted univariate model are presented in Table 4.26 and Table 4.26 b**Error! Reference source not found.** and shown p-values were from the QML estimates.

Table 4.26 b shows separately the estimated parameters for the Moroccan Dirham (MAD) and Kenya's Nairobi 20 Index due to the estimated parameters for the fitted models that were not possible to synchronise and include in one table with those in Table 4.26. From the goodness of fit p-values reported in Table 4.25 , the univariate volatility models chosen adequately fit the data as there is not enough evidence to show autocorrelation or ARCH-effects from both the standardised residuals, their square counterparts and variance clustering of the log data. The ARCH (or GARCH) test mentioned in Table 4.25 is an application of the Ljung-Box test on squared residuals to test for the existence of ARCH effects post fitting a GARCH model. From Table 4.26 and Table 4.26 b, certain facts can be highlighted about the univariates, such as :

- From the significance and values of the persistence parameters (α, β and γ), conditional volatility significantly plays a role in describing the volatility process of each univariate series, indicating the existence of volatility clustering that is averted by using such a volatility model.

- Asymmetry and leverage effects can be considered to be significant and this is a result from the ability of models such as the GJR and EGARCH to model some of the data better than a vanilla or standard GARCH model.

- In most of the univariates, leptokurtosis can be deduced from the significance of the skewness and shape parameters, as where they are applicable, are significant and enable the models in most cases to better fit the data and this is applicable even in cases where the vanilla GARCH is applied.

- Except for XOF, Gold, ZAR, BWP, EGX30 and TND, most skewness or shape parameters (ξ), where t or skewed innovations are used, are significant and low (and $\upsilon \geq 2$) showing that most series do not have a thick tail.

The ensuing step of the IMF method requires that the residuals extracted from each fitted marginal are standardized, transformed and used in determining the joint structure for each economy and the estimation is presented and explained in the ensuing subsection.

Table 4.24 Fitted Univariate GARCH Models

Variable	Z_t	GARCH Family	ARMA (p , q)	GARCH (p , q)	AIC	LLH
Gold	*t*	Exponential	(1,1)	(1,1)	-3.31	404.70
Oil	*sN*	GJR	(1,0)	(1,1)	-2.31	283.61
SALSI	*N*	GJR	(0,0)	(1,1)	-3.43	416.12
ZAR	*st*	Standard	(0,0)	(1,1)	-3.26	397.25
NSE	*N*	GJR	(1,0)	(1,2)	-2.68	327.19
NGN	*N*	GJR	(1,0)	(1,1)	-4.14	502.23
BSEDCI	*t*	Standard	(1,0)	(1,1)	-4.53	548.93
BWP	*st*	Standard	(0,0)	(0,1)	-4.11	497.07
NSE	*st*	Standard	(1,1)	(2,2)	-2.95	363.49
KES	*t*	Standard	(1,0)	(1,1)	-5.58	675.48
EGX30	*st*	Standard	(1,0)	(1,1)	-1.99	242.34
EGP	*st*	Exponential	(1,0)	(1,1)	-6.54	792.89
GSE	*t*	Exponential	(1,0)	(1,1)	-3.51	427.73
GHS	*st*	GJR	(1,0)	(1,1)	-6.26	759.74
Tunindex	*t*	Exponential	(1,1)	(1,2)	-3.94	480.71
TND	*t*	Standard	(1,0)	(1,2)	-4.88	590.86
DZAIR	*t*	Exponential	(0,0)	(1,1)	-4.88	355.18
DZD	*t*	Exponential	(1,0)	(1,1)	-5.86	429.10
MASI	*N*	Exponential	(1,0)	(1,1)	-3.70	405.95
MAD	*t*	Standard	(2,2)	(2,2)	-4.94	543.31
XOF	*st*	Exponential	(1,0)	(1,1)	-4.38	308.36
BRVM-CI	*N*	Standard	(1,0)	(1,2)	-3.39	237.52
ZMK	*st*	Exponential	(1,0)	(1,1)	-3.48	246.16
LuALSI	*t*	Exponential	(1,1)	(1,1)	-3.84	271.23
UGX	*t*	Standard	(1,0)	(1,1)	-4.74	454.85
UALSI	*sN*	GJR	(1,1)	(1,1)	-2.42	236.46
TZS	*st*	Exponential	(1,1)	(1,1)	-6.53	524.54
DSEAI	*st*	Standard	(0,0)	(1,1)	-3.99	320.88
ETB	*st*	Exponential	(0,0)	(1,1)	-7.75	937.18
CDF	*t*	GJR	(1,1)	(1,1)	-5.01	608.07
LYD	*t*	Standard	(0,0)	(1,1)	-5.54	668.90
AOA	*t*	GJR	(1,1)	(1,1)	-5.65	686.10
SDG	*st*	Standard	(1,0)	(1,1)	-6.07	452.06
Khartoum 30	*t*	Standard	(1,0)	(1,1)	-3.83	286.64

Table 4.25: Univariate GARCH Goodness of Fit

Variable	Ljung-Box Std. Residuals			Ljung-Box Squared Std. Residuals			ARCH Test		
	Lag [i] , [i =x* (p+q)+(p+q)-1]								
	[1]	[i, x =2]	[i, x =4]	[1]	[i, x =2]	[i, x =4]	[3]/[2]	[5]/[4]	[7]/[6]
Gold	0.9473	1.0000	0.9996	0.7229	0.9391	0.9553	0.7568	0.9660	0.8944
Oil	0.5037	0.9721	0.9666	0.8703	0.7858	0.4690	0.5741	0.3911	0.2068
SALSI	0.4636	0.6189	0.7442	0.5588	0.8704	0.5639	0.5390	0.7582	0.7029
ZAR	0.9551	0.8109	0.9472	0.8278	0.9340	0.8891	0.9699	0.7572	0.6518
NSE	0.7837	0.8471	0.1497	0.6725	0.4831	0.6027	0.8566	0.9311	0.8896
NGN	0.9334	0.9742	0.9063	0.9704	0.9997	1.0000	0.8414	0.9935	0.9995
BSEDCI	0.2270	0.1707	0.3014	0.7472	0.9362	0.9793	0.4769	0.8435	0.9142
BWP	0.4653	0.2835	0.3948	0.7462	0.7563	0.9506	0.4674	0.8556	0.9300
NSE	0.8491	0.9998	0.9649	0.6777	0.1831	0.1229	0.1277	0.3731	0.5420
KES	0.5182	0.5035	0.1851	0.4735	0.1568	0.3081	0.7157	0.9344	0.9485
EGX30	0.8542	0.9998	0.0963	0.5046	0.6402	0.6797	0.6317	0.3594	0.5416
EGP	0.8811	1.0000	1.0000	0.9329	0.9999	1.0000	0.9337	0.9990	1.0000
GSE	0.1567	0.2094	0.0750	0.4065	0.5623	0.5980	0.4007	0.5839	0.5717
GHS	0.8293	1.0000	0.9998	0.9271	0.9899	0.9993	0.6917	0.9634	0.9944
Tunindex	0.9360	1.0000	0.9741	0.2690	0.3292	0.3726	0.6738	0.3105	0.4284
TND	0.6749	0.8976	0.7932	0.2572	0.1359	0.2695	0.8318	0.9256	0.9341
DZAIR	0.1639	0.1555	0.2371	0.5582	0.9645	0.9734	0.7334	0.9698	0.9781
DZD	0.7482	0.9918	0.6013	0.6838	0.9797	0.9778	0.9632	0.9860	0.9066
MAD	0.1556	0.6222	0.7462	0.5270	0.1134	0.2572	0.8396	0.8515	0.7843
MASI	0.8879	1.0000	0.9391	0.6214	0.8073	0.7218	0.7219	0.8014	0.5539
XOF	0.7979	0.6481	0.5929	0.2891	0.1961	0.2280	0.9236	0.1820	0.2396
BRVM-CI	0.8613	0.7377	0.7678	0.3938	0.1046	0.1058	0.9478	0.1294	0.2123
ZMK	0.1389	0.1418	0.4324	0.8140	0.9784	0.9979	0.7764	0.9460	0.9893
LuALSI	0.7747	0.1418	0.1964	0.8710	0.9481	0.9843	0.6346	0.9364	0.9635
UGX	0.2907	0.6668	0.6832	0.6449	0.9531	0.9766	0.6074	0.8329	0.9137
UALSI	0.2697	0.9369	0.7943	0.7375	0.9875	0.9938	0.9212	0.9750	0.9934
TZS	0.8825	1.0000	0.9999	0.5874	0.9549	0.9940	0.9627	0.9772	0.9959
DSEAI	0.6295	0.8309	0.9637	0.9321	0.9999	1.0000	0.9437	0.9991	1.0000
ETB	0.9559	0.9651	0.9989	0.8656	0.9984	0.9988	0.8642	0.9911	0.9793
CDF	0.9617	1.0000	1.0000	0.9210	0.9998	1.0000	0.9165	0.9986	1.0000
LYD	0.9880	0.9993	0.9726	0.9221	0.9999	1.0000	0.9299	0.9990	0.9976
AOA	0.2572	0.9841	0.6074	0.1359	0.4949	0.5619	0.7235	0.8861	0.6829
SDG	0.8589	1.0000	1.0000	0.8843	0.9992	1.0000	0.8827	0.9945	0.9996
Khartoum 30	0.9037	0.7342	0.7211	0.8838	0.9988	1.0000	0.8878	0.9961	0.9998

Table 4.26: Univariate GARCH Estimates[6]

Variable	Mean	ar (1)	ma(1)	ω	α	δ (1)	δ (2)	γ	ξ - (Skew)	ν - (Shape)
Gold	0.0083 *	0.3971 *	-0.51 *	-0.0114 *	0.1061 *	0.9998 ***		-0.1127 *		13.1132 *
Oil		0.181 ***		0.0014		0.6405 *		0.3394	0.6681 *	
SALSI	0.0077 *			0.0002	0.0569	0.644 *		0.4176 ***		
ZAR	0.0056 ***			0.0004 **	0.1635 **	0.6888 *			1.3837 *	15.8972
NSE	0.0094 **	0.1697 *		0.0008 *		0.6754 *		0.2642 **		
NGN	0.0104 *	0.1661 *		0.0005 *	0.0313 *	0.567 *		-0.277 *		
BSEDCI		0.5008 *			0.2681 **	0.7166 *				4.405 *
BWP						0.998 *			1.1361 *	8.1954 ***
KES		0.1435 ***			0.2253 *	0.7737 *			0.9776 *	4.2246 *
EGX30		0.1462 **				0.999 *			0.9536 *	7.6921 *
EGP	0.0016 *	0.0795 ***		-1.2104 *	-1.0544	0.8027 *		1.7776	1.2275 *	2.01 *
GSE	0.0074 *	0.4728 *		-1.7316	0.0607	0.6553 ***		1.552		2.2688
GHS	0.0033 *	0.7882 *	-0.3649 **		0.877 *	0.7014 *		-1 *	1.2595 *	2.3977 *
Tunindex	0.0068 *	0.7675 *	-0.6575 *	-2.1874 **		0.2023	0.4724 *	0.393 *		4.9388 *
TND		0.1714 **			0.0783	0.8405 *				7.6075 **
DZAIR				-1.6123 **		0.7241 *		1 ***		2.1 *
DZD	0.0035 **	0.2154 *		-1.8345 *		0.7793 *		0.3091 *	1.5394 *	3.0213 *
MASI	0.0082	0.1481		-0.2048 *	0.0464	0.969 *		-0.1734 **		
XOF	0.0079 *	-0.0328 *		-0.0528 *	0.2624 *	0.9883 *		-0.1237 *	1.5673 *	37.1399 ***
BRVM-CI		0.1796 ***		0.0004 ***	0.1814 **		0.5907 **			
ZMK	0.0099 *	-0.1277		-0.3595 *	0.2628 *	0.942 *		-0.0069	1.3221 *	3.8407 ***
LuALSI	-0.006 *	0.7248 *	-0.5789 *	-0.0758 *	-0.4621 *	0.9839 *		-0.274 *		2.5603 *
UGX		0.1464 **		0.0001	0.385 *	0.614 *				3.2857 *
UALSI		0.5551 *	-0.5182 *	0.0032 *		0.1462		0.8639 **	0.7281 *	
TZS	0.0006 **	0.7474 *	-0.6666 *	-0.2539	-0.8819 **	0.9616 *		3.2577 *	1.0504 *	2.01 *
DSEAI	0.0052 **			0.0003	0.74 ***	0.259 ***			1.2143 *	2.6109 *
ETB	0.0036 *			-0.0387 *	0.0543 *	0.99 *		-0.6055 *	1.491 *	2.01 *
CDF		0.9625 *	-0.9564 *		0.9121 *	0.4664 *		-0.759 *		2.6893 *
LYD						0.9942 *				2.1492 *
AOA	0.0008 ***	0.6824 *	-0.1209 ***		0.3987 *	0.9071 *		-0.6244 *		2.1309 *
SDG		0.0137 *		0.0004 **		0.931 *			1.0928 *	2.01 *
Khartoum 30		-0.1514			0.4933 *	0.5057 *				2.7891 *

Table 4.26 b Univariate GARCH Estimates for MAD and NSE

Variable	ar(1)	ar(2)	ma(1)	ma(2)	ω	α(1)	α(2)	δ (1)	δ (2)	ξ - (Skew)	ν - (Shape)
MAD	1.1829 *	-0.8864 *	-1.2217 *	0.9794 *			0.1391	0.3406	0.4992 **		6.5822 *
NSE	0.8331 *		-0.7265 *		0.0007 ***	0.131	0.0128	0.5344	0.1673	0.913 *	3.7793 *

[6] For tables, Table 4.26 and Table 4.26 b the following applies: *** =>Statistical significance at 10%; ** => statistical significance at 5% and * => statistical significance at 1%

4.3.3 GARCH - Copula Estimation

The estimation of a GARCH copula showing the joint dependence structure of the sampled variables is reported in Table 4.27. The results show that except for Kenya at 5% level of significance, all other economies' sampled variables' dependence structure can be estimated using a non-time varying copula.

The estimated dependence measures for both the *t* and Normal copula show negligible differences between them for each economy. The very high values of degrees of freedom (defined as t-DoF (v), fourth column of Table 4.27) seem to suggest in favour of the Normal copula model as being a better fitting copula. To test the best fitting copula, a goodness of fit (GOF) test is performed and the results reported in Table 4.28. The GOF test is based on comparing the estimated copula $C_{est}(u)$ to an empirical distribution function, known as the empirical copula $C_n(u)$, that is derived from the pseudo observations defined as:

$$C_n(u) = \frac{1}{n}\sum_{i=1}^{n} 1\left(\widehat{\boldsymbol{U}}_i \leq u\right), \qquad u \in [0,1]^d \tag{50}$$

The null hypothesis of the GOF test can be defined as follows:

$$H_{null} : C_{est}(u) \in \{ C_\theta(u) \}, \quad u \in [0,1]^d$$

The GOF test uses the difference between the estimated copula and an empirical copula under the assumption that the null hypothesis holds. The test statistic can be defined as follows:

$$S_n = \sum_{i=1}^{n}\left[C_{est}\left(\widehat{\boldsymbol{U}}_i\right) - C_n\left(\widehat{\boldsymbol{U}}_i\right)\right]^2 \tag{51}$$

In equation (51), the estimated pseudo observations, $\hat{\boldsymbol{U}}_i's$, can be defined as in equation (28). The *p*-value used as a decision criterion is estimated by bootstrapping. Hofert et al. (2018) describe the resampling steps involved in finding the p-value as initially generating n pseudo-observations from which parameters are estimated to compute the test statistic in (51) this process is repeated k times, k ∈ $\{1, \dots, N\}$, with N being a large integer. Each k^{th} step uses the estimated copula and yields an estimated parameter from the pseudo observations, ${S_n}^{(k)}$. From each of the steps, the p – value is given by the following:

$$\frac{1}{N+1}\left(\frac{1}{2}+\sum_{i=1}^{N} 1\left(S_n^{(k)} \geq S_n\right)\right)$$

Table 4.27: GARCH Copula Estimation

Economy	**Copula Estimate**		
	N	***t***	***t - DoF***
Algeria	-0.0161	-0.0141	31.714
Angola	0.0169	0.0167	155.683
Botswana	-0.0465	-0.0451	11.740
DRC	0.0735	0.0788	18.393
Cote d'Ivoire	-0.0981	-0.0942	17.590
Arab Rep. of Egypt	0.0439	0.0387	8.101
Ethiopia	0.0326	0.0310	25.823
Ghana	0.0266	0.0261	127.499
Kenya	-0.0212	-0.0161	16.090
Libya	-0.1679	-0.1657	9.138
Morocco	-0.0741	-0.0713	10.167
Nigeria	0.0237	0.0164	11.413
South Africa	-0.0100	-0.0107	10.552
Sudan	-0.0108	-0.0098	29.904
Tanzania	0.2253	0.2365	4.316
Tunisia	-0.0711	-0.0683	11.458
Uganda	0.0233	0.0242	14.815
Zambia	-0.0166	-0.0160	31.385

Table 4.28: GOF and Consistency Tests

Economy	Copula Non-consitency Test	Copula GOF Test N	Copula GOF Test t
		(p - values)	
Algeria	0.1124	0.4850	0.5709
Angola	0.9875	0.1194	0.1324
Botswana	0.4630	0.7577	0.6938
DRC	0.7907	0.2353	0.3741
Cote d'Ivoire	0.8487	0.2512	0.3871
Arab Rep. of Egypt	0.4381	0.3452	0.3641
Ethiopia	0.5380	0.0115	0.0115
Ghana	0.7408	0.8097	0.7977
Kenya	0.0085	0.9316	0.9545
Libya	0.7398	0.0045	0.0015
Morocco	0.5360	0.0994	0.1204
Nigeria	0.9675	0.0165	0.0115
South Africa	0.4910	0.1094	0.1154
Sudan	0.5280	0.0395	0.0295
Tanzania	0.2113	0.0005	0.0005
Tunisia	0.7258	0.0325	0.0445
Uganda	0.2852	0.8626	0.8267
Zambia	0.5719	0.5539	0.5350

From the results of Table 4.28, at 5% level of significance a different copula, other than the *t* and Normal copulas, would be required to fit the dependence structure of univariate GARCH models fitted for Ethiopia, Libya, Nigeria, Sudan, Tanzania and Tunisia and this based on *p*-values of the copula GOF tests for the countries being quite low. For other countries, there seem to be not enough evidence to dispute the ability of both the *t* and Normal copula to describe the dependence and this is due to the none-elliptic distribution in the returns data. In the ensuing subtopic a copula multivariate GARCH is presented, estimated and discussed. In the CMGARCH the extracted bivariate dependence and joint estimation becomes the salient point of discussion.

4.3.4 Copula based Multivariate GARCH

In this subsection the Student-*t* and Normal copulas are again used in coupling the univariate probability integral transformed standardised residuals. The two copulas are tested for better fit based on AIC and likelihood and their results are reported in Table 4.29.

The results do not give a clear indication of a better copula model to use between the two because in the fitted copula-DCC models, the AIC (and LLH) values have a negligible difference in value. With the small differences reported, both elliptical copulas are then used in describing the copula-GARCH structure. The ensuing step checks if either the constant or conditional correlation assumption is useful assumption when describing the correlation amongst the sampled variables. The conditional correlation assumption comes from testing the statistical significance of DCC-GARCH joint scalar parameters that are useful in determining the dynamic correlation pattern. The p-value results from the conditional correlation test for each model are reported for each economy in Table 4.30 under columns α_1 and α_2. For countries such as Angola, Ethiopia, Kenya, Libya, Morocco, Sudan and Tunisia; the DCC joint parameters' p-values show that the constant correlation assumption would fit their correlation process as the scalar parameters are not that different to zero from a 5% level of significance. There are cases where at least one of the scalar joint parameters is significant at 5% and this can be observed in the economies of Algeria, Botswana, Ivory Coast, A.R Egypt, Ghana, Nigeria, Uganda, South Africa, Tanzania and Zambia. The above-mentioned cases apply to both the fitted t-copula-DCC and Normal-Copula DCC.

Table 4.29: AIC and LLH from copula DCC

Economy	**LLH**		**AIC**	
	Copula DCC GARCH			
	t	***N***	***t***	***N***
Algeria	1 184.62	1 183.84	-16.12	-16.12
Angola	1 270.95	1 270.78	-10.44	-10.45
Botswana	1 757.78	1 756.22	-14.47	-14.47
DRC	1 298.38	1 298.02	-10.62	-10.64
Cote d'Ivoire	946.10	946.25	-13.48	-13.49
Arab Rep. of Egypt	1 671.84	1 665.64	-13.73	-13.69
Ethiopia	1 590.99	1 590.11	-13.10	-13.10
Ghana	1 814.11	1 814.18	-14.93	-14.94
Kenya	1 714.79	1 713.98	-14.11	-14.11
Libya	1 365.81	1 365.00	-11.24	-11.24
Morocco	1 585.60	1 584.30	-14.47	-14.47
Nigeria	1 552.80	1 550.08	-12.76	-12.74
South Africa	1 537.71	1 536.46	-12.63	-12.63
Sudan	1 029.43	1 029.86	-13.71	-13.73
Tanzania	1 237.54	1 227.67	-15.36	-15.25
Tunisia	1 786.74	1 784.60	-14.69	-14.68
Uganda	1 231.86	1 230.61	-12.74	-12.73
Zambia	889.66	889.08	-12.64	-12.64

Table 4.30: Copula DCC Correlation Joint Parameters

Economy	*t - Copula*			*N - Copula*	
	(p- values)				
	α_1	**α_2**	**ν - (Shape)**	**α_1**	**α_2**
Algeria	0.9852	0.0000	0.2442	0.9967	0.0000
Angola	1.0000	0.9930	0.9841	0.9747	0.9263
Botswana	0.7301	0.0000	0.1676	1.0000	0.4624
DRC	0.9982	0.0000	0.8597	0.9914	1.0000
Cote d'Ivoire	0.9952	0.0000	0.0138	0.8855	0.0000
Arab Rep. of Egypt	0.9746	0.0000	0.9571	0.9499	0.0279
Ethiopia	1.0000	0.7540	0.9366	0.9658	0.9075
Ghana	0.9999	0.0000	0.0001	0.9939	0.0000
Kenya	0.9997	0.9972	0.3153	0.9818	0.9965
Libya	0.9996	0.3168	0.9969	0.9735	0.4688
Morocco	0.8873	0.5356	0.9819	1.0000	0.9578
Nigeria	0.9989	0.0000	0.0671	0.9561	0.0000
South Africa	0.9728	0.0349	0.9849	0.9712	0.0649
Sudan	0.0662	0.0807	0.1732	0.0542	0.0599
Tanzania	0.0233	1.0000	0.0209	0.0144	1.0000
Tunisia	0.9966	0.9334	0.9919	0.9918	0.9385
Uganda	0.9998	0.0000	0.3233	0.9945	0.0000
Zambia	0.8293	0.0000	0.8933	0.8206	0.0000

4.3.4.1 Dynamic and Constant Conditional Correlation

The elliptical copulas have been used to fit the volatility structure of the data from which covariance, dependence and correlation can be extracted. In this section, a visual of the relationship amongst the variables is created on a bivariate level using conditional correlation extracted from the above fitted Student *t*-DCC GARCH model. From the relationship established between dependence coefficients, Kendall’s tau and Pearson’s correlation, one can conclude that the dynamic tau coefficient on a bivariate level would also flow or be distributed similarly to the dynamic correlation that is visually established in the figures below. In each chart, notable global (some, USA and Europe initiated) financial events have been embedded in the correlation charts to show some interesting changes in the bivariate association pre, during and post each financial crisis. The following events (and used starting dates in parentheses) have been orderly added to each chart:

- Technology stocks bubble that took place in the year 2000 (March 2000)
- Terror related incident that took place at USA (September 2001)
- 2008 financial crisis (January 2008)
- 2009 Eurozone bond crisis (December 2009)
- Oil price plunge of 2014 (July 2014)

Due to the results of the DCC parameters presented in Table 4.30 which show that a CCC model is appropriate, some of the y-axis values have been scaled in the visuals as the correlation process change occurs in small quantities around an average conditional correlation value. An example would be the correlation visuals for the economies of South Africa and Algeria, where the average change in conditional correlation for each country is high and recordable in the y-axis for South African while that of Algeria evolves around its average values for each bivariate relationship. The adjusted correlation value for each economy is mathematically expressed in equation (52) for each estimated DCC element at time *i* for a vector of length T.

$$\widetilde{D}_i = DCC_i\, 10^{10} - 10^3 \left(\sum_{i=1}^{T} \frac{DCC_i}{T} \right) 10^7 \tag{52}$$

The scaled correlation value allows for small changes in correlation and dependence to be visualised and this is applied for sampled economies except for Egypt, South Africa, Tanzania, Libya and Zambia where the actual correlation levels and quantities are used. Table 4.31 and Table 4.32 offer an initial view of the average correlation and Kendall tau values that are extracted from the Student t-DCC GARCH models. The volatility inclusive association values differ to those that were presented on a return level in section 4.2.2, an example are the tau measures for the relationship between the currency and stock market of Zambia, $\rho_{\tau_{Returns}} = -0.038$ and $\rho_{\tau_{Volatility}} = 0.022$. Due to the one-to-one relationship between the two dependence measures, shown in equation (43), there is no change in the signage of the values, but the quantities differ. In Table 4.31 and Table 4.32, each economy's fitted model, parameter estimates, and the parameters' p-value based significance are presented with their conditional dependence process. In all the fitted t-copula DCC models, as applied in earlier sections, a "*" symbolises a statistical significance level of 1%, " ** " for 5% and " *** " for 10%.

Table 4.31 Average Dynamic Conditional Correlation

Economy	Stock Market			Exch. Rates		Gold & Crude Oil
	Exch. Rates	Gold	Crude Oil	Gold	Crude Oil	
Algeria	1.85%	-6.72%	-1.90%	-15.50%	-11.66%	8.83%
Angola	-	-	-	-3.50%	-2.23%	-10.38%
Botswana	12.01%	-1.16%	-0.74%	-30.94%	-20.55%	13.82%
Cote d'Ivoire	-13.72%	-1.90%	9.29%	-32.96%	-26.34%	9.82%
DRC	-	-	-	7.89%	-1.74%	14.27%
Egypt Arab Rep.	7.27%	14.98%	19.69%	-10.72%	-0.72%	13.83%
Ethiopia	-	-	-	1.50%	2.27%	13.56%
Ghana	-1.06%	1.65%	7.93%	-7.42%	0.77%	12.01%
Kenya	-4.31%	6.41%	-7.52%	-11.04%	-11.50%	13.31%
Libya	-	-	-	-39.58%	-18.84%	13.15%
Morocco	-4.13%	3.46%	-0.12%	-37.48%	-22.90%	12.15%
Nigeria	-3.89%	2.72%	11.52%	3.01%	-12.87%	14.88%
South Africa	-16.21%	20.45%	18.73%	-29.40%	-17.84%	10.40%
Sudan	8.36%	-12.26%	3.23%	-10.38%	2.41%	23.82%
Tanzania	3.29%	1.96%	4.24%	4.35%	17.10%	79.72%
Tunisia	1.27%	0.04%	0.09%	-41.54%	-14.19%	12.32%
Uganda	2.60%	6.95%	10.50%	-7.02%	-19.12%	17.58%
Zambia	3.41%	-12.44%	13.96%	-13.33%	-13.13%	9.91%

Table 4.32 Average Kendall's Tau

Economy	Stock Market			Exch. Rates		Gold & Crude Oil
	Exch. Rates	Gold	Crude Oil	Gold	Crude Oil	
Algeria	1.18%	-4.28%	-1.21%	-9.91%	-7.44%	5.63%
Angola	-	-	-	-2.23%	-1.42%	-6.62%
Botswana	7.67%	-0.74%	-0.47%	-20.03%	-13.18%	8.83%
Cote d'Ivoire	-8.76%	-1.21%	5.92%	-21.38%	-16.97%	6.26%
DRC	-	-	-	5.03%	-1.11%	9.12%
Egypt Arab Rep.	4.63%	9.57%	12.62%	-6.84%	-0.46%	8.83%
Ethiopia	-	-	-	0.96%	1.44%	8.66%
Ghana	-0.67%	1.05%	5.05%	-4.73%	0.49%	7.67%
Kenya	-2.75%	4.08%	-4.79%	-7.05%	-7.33%	8.50%
Libya	-	-	-	-25.90%	-12.07%	8.40%
Morocco	-2.63%	2.20%	-0.08%	-24.46%	-14.71%	7.76%
Nigeria	-2.48%	1.73%	7.35%	1.91%	-8.21%	9.51%
South Africa	-10.37%	13.11%	12.00%	-19.00%	-11.42%	6.63%
Sudan	5.33%	-7.82%	2.06%	-6.62%	1.53%	15.31%
Tanzania	2.10%	1.25%	2.70%	2.77%	10.94%	58.74%
Tunisia	0.81%	0.02%	0.06%	-27.27%	-9.07%	7.86%
Uganda	1.66%	4.43%	6.69%	-4.47%	-12.25%	11.25%
Zambia	2.17%	-7.94%	8.92%	-8.51%	-8.39%	6.32%

To assess the dynamic relationship amongst the sampled variables, each economy's main exports are referenced (mainly in parentheses) to guide the discussion around potential export diversification risk highlighted by Deaton (1999). In this study however, there are cases where main exports of a single economy alone cannot account for the association relationship observed and this due to the inclusion of a regional currency and stock exchange, the XOF (the non-sampled XAF) and BRVMCI represented summarily under Côte d'Ivoire. Côte d'Ivoire has its currency negatively dependent (or correlated) to both oil and gold, $\rho_\tau = -0.17$ and $\rho_\tau = -0.21$, respectively. This negative relationship can be attributed to having a mixture of exported commodities by the regional constituents and implies that the price (as shown in Table 4.14) and volatility of the commodities generally has a positive relation with the regional currency. For instance, within the region there are economies; Benin (gold), Burkina Faso (gold), Guinea-Bissau (cashew nuts), Mali (gold), Niger (gold), Senegal (gold and oil), Togo (gold and oil) and Côte d'Ivoire (cocoa). All the main exports highlighted in brackets cannot however be said to be influential in relating the BRVMCI to the sampled commodities because there is a nonhomogeneous relationship for the stock market performance index with both oil and gold, $\rho_\tau = 0.06$ and $\rho_\tau = -0.01$, respectively. The negative dependence relation between the BRVMCI and XOF is also stable and has time varying changes that are quite small around the average tau value of $\rho_\tau = -0.09$. The implication of the negative relationship is that the region's local currency is likely to appreciate as the stock market soars.

Tanzania (gold and tobacco) is the only sampled economy that on average shows dynamically positively dependent relationships amongst the sampled variables. The co-movement relationships start at relatively low values, that are close to zero and negative, then grow abruptly around 2009 for the TZS, oil and gold relationships but around 2014 for the DSEAI, oil and gold relationships. The relationship between the TZS and DSEAI also peaks at or around the duration of the 2014 oil price plunge and during this period there is a trend increase in the TZS, DSEAI and oil bivariate relationships. Like Tanzania, Ethiopia (gold and coffee) has a positive relatively small dynamic dependence relationship with both gold and oil, $\rho_\tau = 0.0096$ and $\rho_\tau = 0.014$, respectively. The association has a step change that shows an increase in the currency and commodity relation within the 2008 financial crisis, but has a varying reaction post the 2014 oil price crash where oil and ETB association increased while the ETB and gold decreased.

A.R Egypt (oil), Tunisia (cotton and olive oil) and Uganda (gold and cocoa) are economies that each have on average a positive relationship between their stock markets and all other variables and a negative dependence relationship between their currencies and sampled commodities. For Tunisia there is a stable dependence measure that is observable for all variables and is seen to be fluctuating around its average over the sampled period. For A.R Egypt, the measure of association between the EGP and EGX30 drops around 2004 and 2005 then starts increasing after the 2008 market crisis. During the 2008 financial crisis there is also a notable stepwise change in the gold, oil and EGx30 relationship that is a sign of a market reaction as the relationship amongst the variables reaches their peak dependence and sharply decreases after each highlighted oil market crash. Uganda also experiences an abrupt change that occurs during the 18 months from the beginning of January 2008, the change is noticeable by the stepwise altered trend amongst all the variables that gets sustained post the crisis period.

In most of the fitted models there is a generally negative relationship that exists between currencies and the sampled commodities, which signals that positive (negative) change in the prices of the commodities results in local currency appreciation (depreciation). For crude oil, there are special cases such as those mentioned above for Tanzania and Ethiopia and for economies Sudan (oil and gold) and Ghana (gold, cocoa and oil), where oil is positively associated with currency showing that there is a likelihood of the local currency to depreciate (appreciate) as crude oil prices move up. The fitted models for Ghana and Sudan show that the association measures for each variable oscillate around the average and each economy's variables experienced a shift during the 18 months period from January 2018. Like the SDG, Sudan's Khartoum 30 is also respectively both negative and positively related to gold and oil. Both gold and oil for an economy like Sudan, are crucial commodities as they account for a high ratio of exported goods that have shown varying association to its currency and equities markets over the sampled period. Sudan's SDG is also inversely associated with its local stock index the Khartoum 30. For gold, Nigeria (oil) and D.R. Congo (copper) are economies with fitted models indicating a positive association between their currencies and gold. For Nigeria, both the 2008 and 2014 oil price plunge show a market reaction that somehow proves gold as a currency haven for the economy, this can be observed in the positive increase in the NGN and Gold association that occurs during and post the highlighted oil price plunges. The relationship between NGN and gold shows a stable movement around the average association measure that has a step change during the 2008 and 2014 oil crises. The step change is also observable in the association amongst other variables in the model for the Nigerian economy. The expectation for Nigeria would be a high association amongst oil, NGN and NSE due to oil and gas being exported goods that significantly account for the country's exports sector. DRC's CDF has associations amongst oil and gold that are relatively stable around the mean association value but show also shows a step change that is visible during the 2008 and 2014 oil crises for both commodities. These changes, as DRC is a copper exporter, could be signals of changing demand of copper that is brought by the change in the price of (production) additives and a co-movement in the metal's markets in general. The currencies of Libya (oil and diamonds) and Angola (oil and gas) also have a negative co-movement relationship with the sampled commodities. For Libya there is an increase in the negative association that changes direction after 2009, but both the 2008 and 2014 oil price plunge had a visible impact in the currency markets. For

Angola there is also a downward trend that is sustained by the AOA and gold relationship pre-2009 that also changes direction after 2009 while that of AOA and oil has an upward trend until the beginning of the 2014 oil price plunge.

There is not a clear association amongst African equity markets, their currencies and the sampled commodities. Excluding the economies whose stock market relationship has been mentioned above, there is a negative association between equity and currency markets for Kenya (oil, tea and flowers), Morocco (vehicles, chemical acids and electrical equipment) and South Africa (gold and platinum) this means that the stock markets have a positive association with their local currencies. Variables in the model for Kenya show small co-movements around the average linear association measure. The model fitted for Morocco shows a trend changes that occur in around 2004 and 2011 for the MASI, gold and oil relationship; mid 2009 for the MAD, oil and gold relationship ; and a downward trend in the MAD and MASI association that starts during the 2014 oil price plunge. South Africa's fitted variables show significant changes in their levels of association during the sampled period, where the included financial crises only show an impact in the ZAR and gold association during the 2008 crisis. A market reaction is also seen in the abrupt downward trend of association that occurs around the 2014 oil price plunge for all variables. The stock markets of Algeria (oil and gas) and Botswana (diamonds) have low negative average dependence measure between them, crude oil and gold that are below 5%. Algeria's variables show small changes in trend and direction that take place just before and during the 2008 financial crisis. For Botswana there is a downward decreasing level of positive association for the BWP and the domestic BSEDCI, the implication of the positive association is unique and is relatively the largest and implies that the domestic index is linked negatively to the local currency such that an increase in the stock index is associated with a decrease in the local currency. The remainder of the variables in Botswana, have an association that revolves around the mean dependence measure throughout the sampled period with slight reversion during the included oil crises periods. The model fitted for Zambia (copper) shows a unique association amongst variables. The rebasing of the currency shows to have had an impact that affected all markets around 2011 while the 2014 oil price plunge shows to have affected the association amongst equity, currency, and gold markets, though this is not fully visible in the currency and gold markets.

For most fitted models, except for the model fitted for Angola, there is a generally positive dependence relation between oil and gold returns and this relation is true also from a return's perspective. The relationship in absolute value is relatively high for Tanzania and lowest for Algeria (respectively, $\rho_\tau = 0.587$ and $\rho_\tau = 0.056$) but can be observed to have a downward trend for most economies post the 2014 oil price crash, symbolising either an increase in the negative or (by lowering to zero) a decrease in level of the relationship.

Table 4.33 Fitted MGARCH for Algeria

Variable	Parameter	Estimate
DZAIR	ω	-1.9133 *
	α (1)	0.0575
	δ (1)	0.6507 *
	γ	1.343 **
	ν - (Shape)	2.1 *
DZD	ω	-3.7742
	α (1)	0.2359
	δ (1)	0.5471
	γ	0.0991
	ξ - (Skew)	1.7726 *
	ν - (Shape)	4.1372 **
Gold	ω	-1.2714
	α (1)	-0.0687
	δ (1)	0.7889 *
	γ	0.2831 ***
	ν - (Shape)	9.4093 ***
Oil	ω	0.0013
	α (1)	0.1207
	δ (1)	0.4762 **
	γ	0.3994 ***
	ξ - (Skew)	0.6565 *
DCC	α_1	0.0000
	α_2	0.9811 *
	ν - (Joint Shape)	22.6571

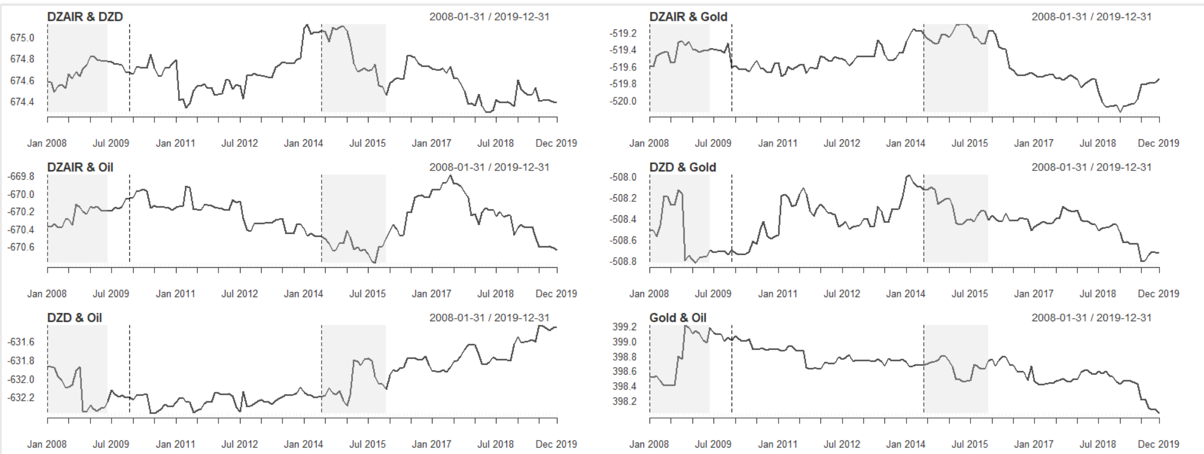

Figure 4.38 Algeria Dynamic Conditional Correlation

Table 4.34 Fitted MGARCH for Angola

Variable	Parameter	Estimate
	ω	0.0003
	α (1)	1
AOA	δ (1)	0.3948
	γ	-0.9031
	ν - (Shape)	2.5085 *
	ω	-0.0134 *
	α (1)	0.092
Gold	δ (1)	0.9999 *
	γ	-0.1018 *
	ν - (Shape)	9.777 *
	ω	0.0042 **
	α (1)	0.0000
Oil	δ (1)	0.0707
	γ	0.5231
	ξ - (Skew)	0.6903 *
	α_1	0.0000
DCC	α_2	0.9283
	ν - (Joint Shape)	43.7867

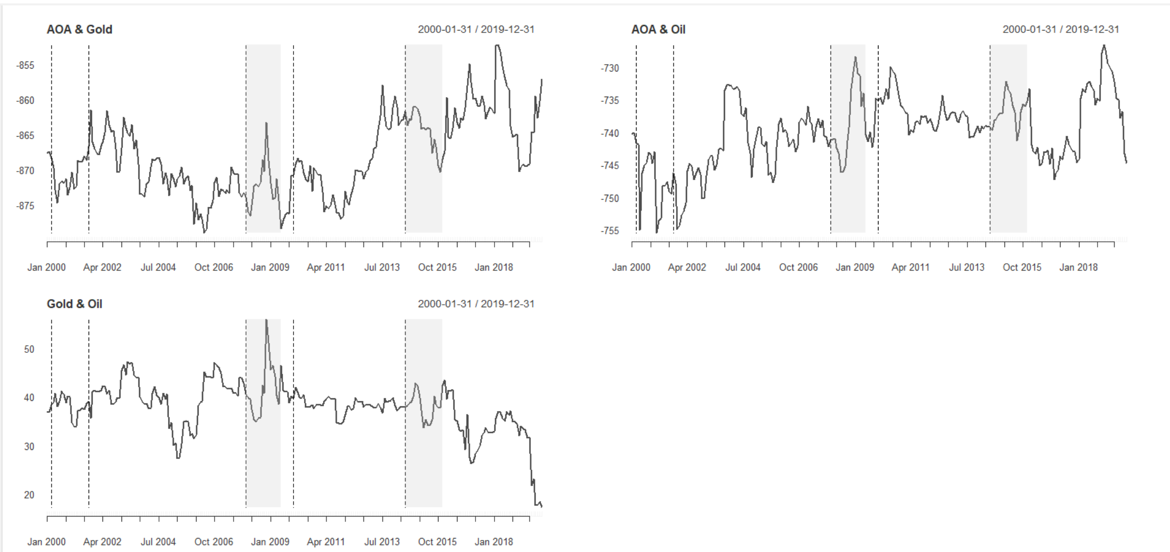

Figure 4.39 Angola Dynamic Conditional Correlation

Table 4.35 Fitted MGARCH for Botswana

Variable	Parameter	Estimate
BSEDCI	ω	0.0000 **
	α (1)	0.2304 **
	δ (1)	0.7407 *
	ν - (Shape)	5.1133 *
BWP	ω	0.0000
	δ (1)	0.9984 *
	ξ - (Skew)	1.1612 *
	ν - (Shape)	8.3175 ***
Gold	ω	-0.0057 *
	α (1)	0.0604 *
	δ (1)	0.9999 *
	γ	-0.0412 *
	ν - (Shape)	25.5352
Oil	ω	0.0042
	α (1)	0.0000
	δ (1)	0.0678
	γ	0.5378
	ξ - (Skew)	0.688 *
DCC	α_1	0.0000
	α_2	0.9581 *
	ν - (Joint Shape)	19.6967

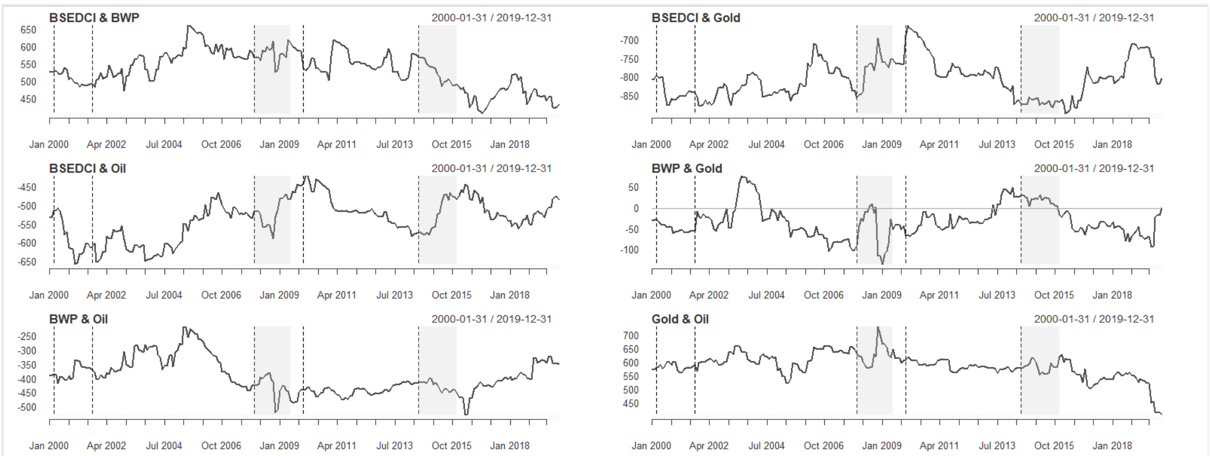

Figure 4.40 Botswana Dynamic Conditional Correlation

Table 4.36 Fitted MGARCH for Côte d'Ivoire

Variable	Parameter	Estimate
BRVM CI	ω	0.0003 **
	α (1)	0.1647 ***
	δ (1)	0.0000
	δ (2)	0.6467 *
XOF	ω	-0.0084 *
	α (1)	0.2003 *
	δ (1)	1 *
	γ	-0.1137 *
	ξ - (Skew)	1.2872 ***
	ν - (Shape)	35.1191
Gold	ω	-0.7421
	α (1)	0.0076
	δ (1)	0.8794 *
	γ	0.2785
	ν - (Shape)	12.6547
Oil	ω	0.0006
	α (1)	0.0000
	δ (1)	0.7519 *
	γ	0.2727
	ξ - (Skew)	0.7204 *
DCC	α_1	0.0000
	α_2	0.9998 *
	ν - (Joint Shape)	49.9989 **

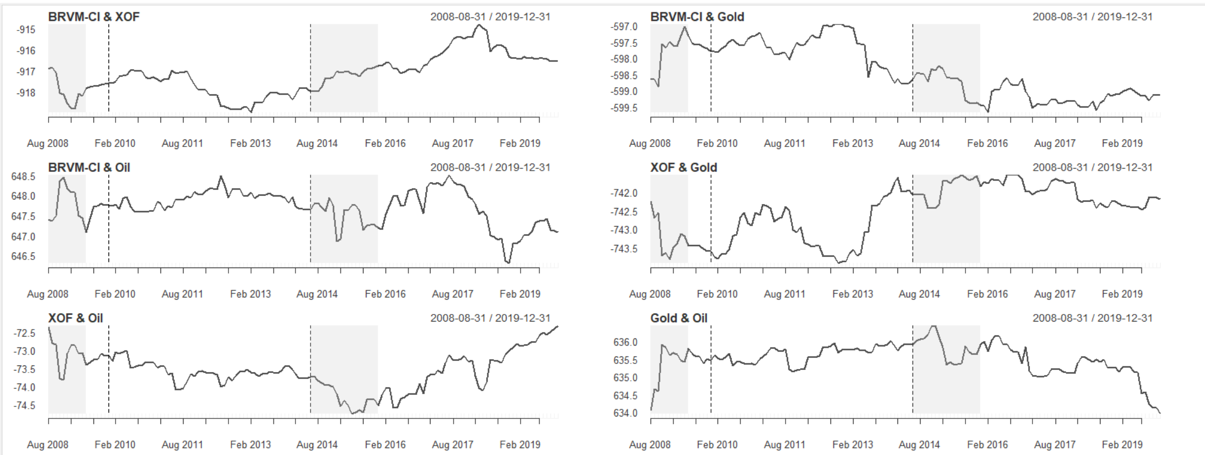

Figure 4.41 Côte d'Ivoire Dynamic Conditional Correlation

Table 4.37 Fitted MGARCH for Dem. Rep. of Congo

Variable	Parameter	Estimate
CDF	ar (1)	0.9625 *
	ma(1)	-0.9564 *
	ω	0.0000
	α (1)	0.9121 *
	δ (1)	0.4664 *
	γ	-0.759 *
	ν - (Shape)	2.6893 *
Gold	Mean	0.0074 *
	ar (1)	0.4642 *
	ma(1)	-0.5545 **
	ω	-0.0165 *
	α (1)	0.0955 *
	δ (1)	0.999 *
	γ	-0.0867 *
	ν - (Shape)	11.1166 *
Oil	ar (1)	0.1809 **
	ω	0.0014
	α (1)	0.0000
	δ (1)	0.6405 *
	γ	0.2539
	ξ - (Skew)	0.6681 *
DCC	α_1	0.0000
	α_2	0.9994 *
	ν - (Joint Shape)	49.9941

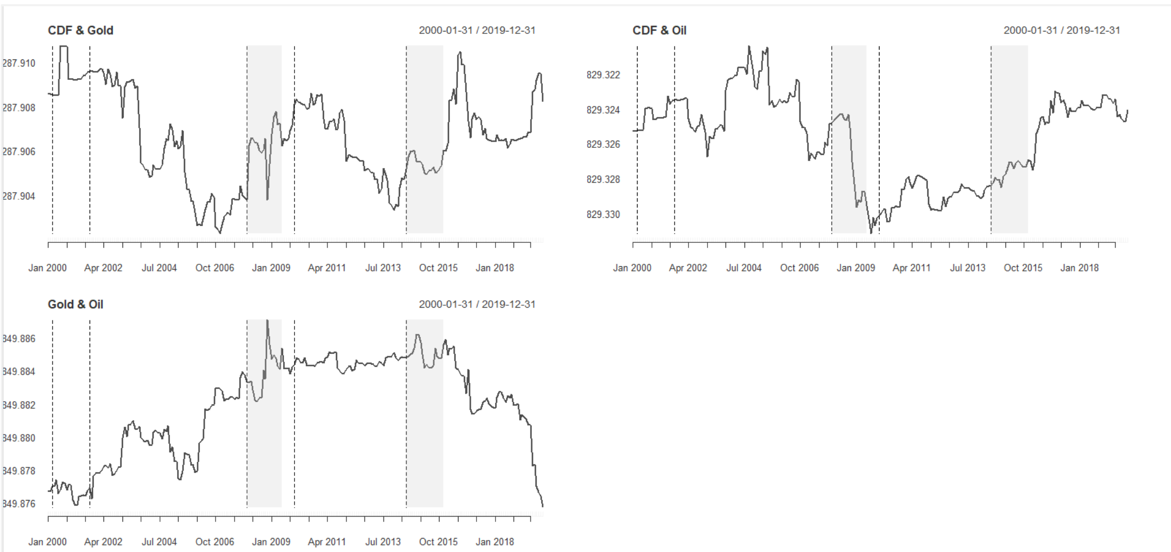

Figure 4.42 Dem. Rep. of Congo Dynamic Conditional Correlation

Table 4.38 Fitted MGARCH for Arab Rep. of Egypt

Variable	Parameter	Estimate
EGx30	ω	0.0000
	α (1)	0.0000
	δ (1)	0.999 *
	ξ - (Skew)	0.9979 *
	ν - (Shape)	7.4353 *
EGP	ω	-0.1453 *
	α (1)	-0.114 ***
	δ (1)	0.9701 *
	γ	0.1977 *
	ξ - (Skew)	1.6919 *
	ν - (Shape)	2.0197 *
Gold	ω	-0.0119 **
	α (1)	0.0967 *
	δ (1)	0.9999 *
	γ	-0.0924 **
	ν - (Shape)	9.362
Oil	ω	0.0037
	α (1)	0.0000
	δ (1)	0.1715
	γ	0.4443
	ξ - (Skew)	0.6258 *
DCC	α_1	0.0054
	α_2	0.949 *
	ν - (Joint Shape)	12.3214

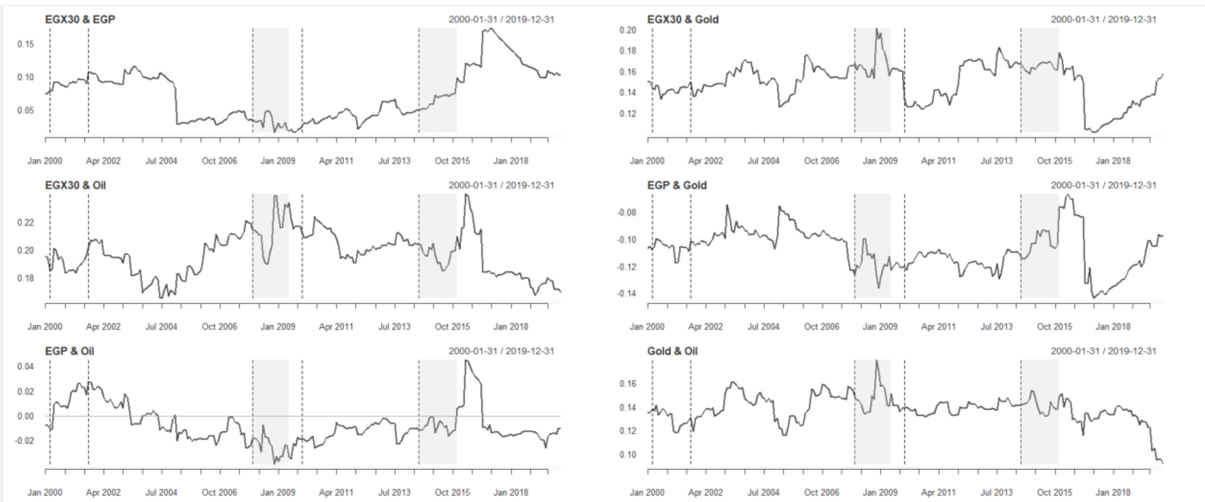

Figure 4.43 Arab Rep. of Egypt Dynamic Conditional Correlation

Table 4.39 Fitted MGARCH for Ethiopia

Variable	Parameter	Estimate
ETB	ω	-0.3139 *
	α	-0.2041 *
	δ (1)	0.9572 *
	γ	0.1756
	ξ - (Skew)	1.9878 *
	ν - (Shape)	2.0557 *
Gold	ω	-0.0096 *
	α	0.0882 *
	δ (1)	0.9999 *
	γ	-0.0791 *
	ν - (Shape)	10.1002 *
Oil	ω	0.0042 *
	α	0.0000
	δ (1)	0.0719
	γ	0.5257 ***
	ξ - (Skew)	0.6889 *
DCC	α_1	0.0000
	α_2	0.9365
	ν - (Joint Shape)	25.7773

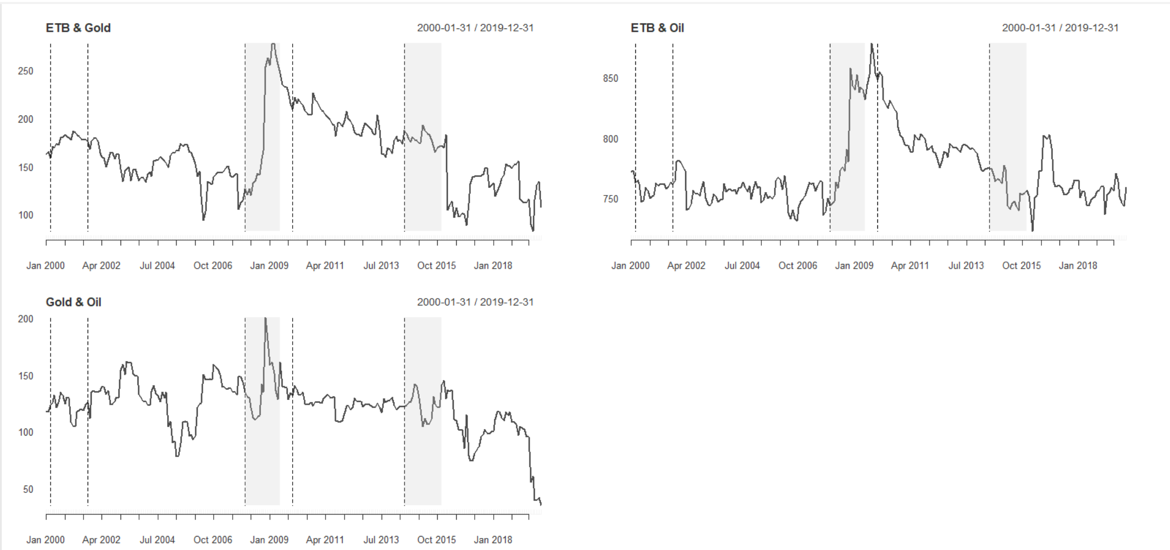

Figure 4.44 Ethiopia Dynamic Conditional Correlation

Table 4.40 Fitted MGARCH for Ghana

Variable	Parameter	Estimate
	Mean	0.0074 *
	ar (1)	0.4727 *
	ω	-1.7331
GSE	α	0.0605
	δ (1)	0.6553 *
	γ	1.5493
	ν - (Shape)	2.2698 ***
	Mean	0.0046 *
	ar (1)	0.732 *
	ma(1)	-0.3095 *
	ω	0.00001 *
GSE	α	0.9999*
	δ (1)	0.533 *
	γ	-0.8908 *
	ξ - (Skew)	1.4143 *
	ν - (Shape)	2.5692 *

Variable	Parameter	Estimate
	Mean	0.0083 *
	ar (1)	0.4427 *
	ma(1)	-0.5166 *
	ω	-0.0241 *
Gold	α	0.1113 *
	δ (1)	0.9978 *
	γ	-0.1068 *
	ν - (Shape)	12.6694 *
	ar (1)	0.181 **
	ω	0.0014
Oil	δ (1)	0.6405 *
	γ	0.2539
	ξ - (Skew)	0.6681 *
	α_1	0.0000
DCC	α_2	0.003
	ν - (Joint Shape)	50

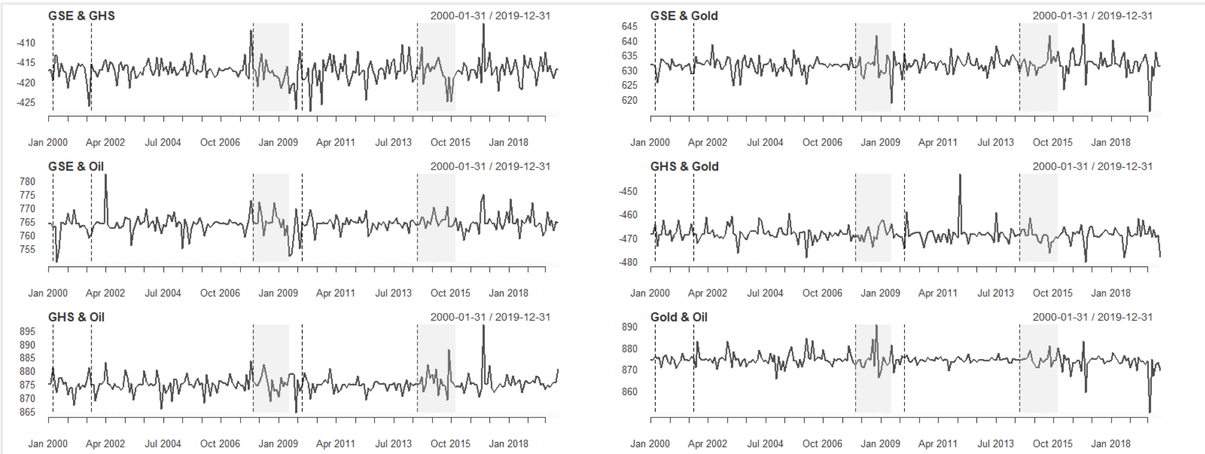

Figure 4.45 Ghana Dynamic Conditional Correlation

Table 4.41 Fitted MGARCH for Kenya

Variable	Parameter	Estimate
NSE	ω	0.0005
	α (1)	0.1167 ***
	α (2)	0.0239
	δ (1)	0.7284
	δ (2)	0.0000
	ξ - (Skew)	0.9373 *
	ν - (Shape)	4.5143 *
KES	ω	0.0000
	α (1)	0.381 **
	δ (1)	0.618 *
	ν - (Shape)	3.3841 *
Gold	ω	-0.0494 *
	α (1)	0.1149
	δ (1)	0.9937 *
	γ	-0.1112
	ν - (Shape)	7.096 *
Oil	ω	0.0047 *
	α (1)	0.0000
	δ (1)	0.0077
	γ	0.4435 **
	ξ - (Skew)	0.6843 *
DCC	α_1	0.0000
	α_2	0.0004
	ν - (Joint Shape)	50

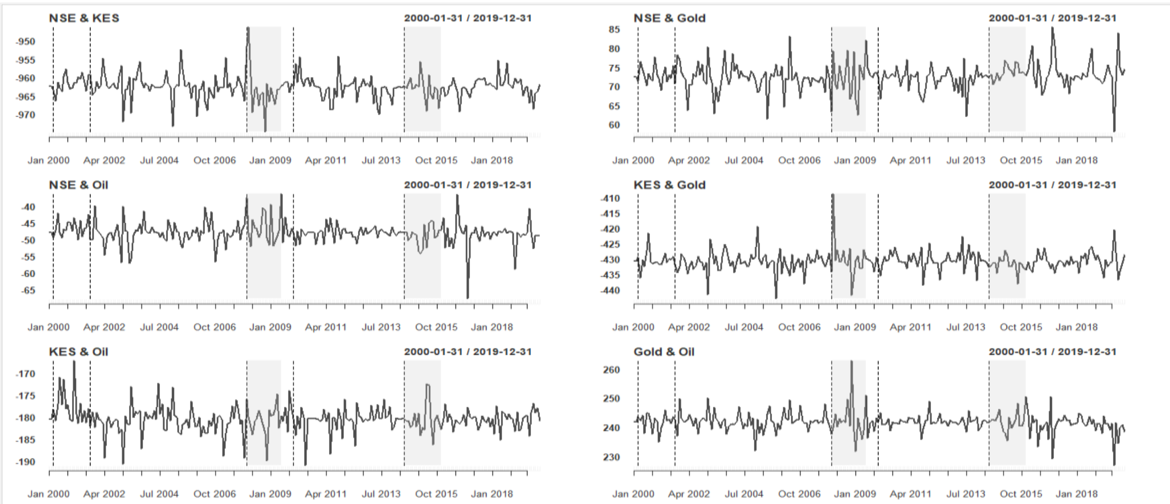

Figure 4.46 Kenya Dynamic Conditional Correlation

Table 4.42 Fitted MGARCH for Libya

Variable	Parameter	Estimate
LYD	ω	0.0000
	α (1)	0.0002
	δ (1)	0.9933 *
	ν - (Shape)	2.2006 *
Gold	ω	-0.0213 *
	α (1)	0.1118
	δ (1)	0.9986 **
	γ	-0.1069 *
	ν - (Shape)	20.8727
Oil	ω	0.0042 *
	α (1)	0.0000
	δ (1)	0.0729
	γ	0.5262 ***
	ξ - (Skew)	0.6875 *
DCC	α_1	0.0003
	α_2	0.9576
	ν - (Joint Shape)	17.9682

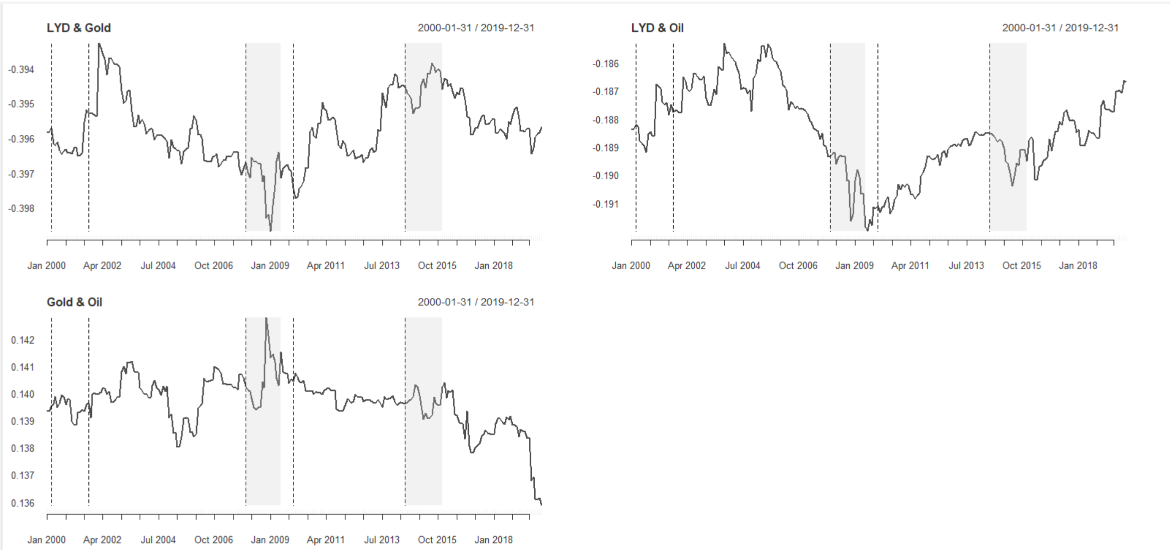

Figure 4.47 Libya Dynamic Conditional Correlation

Table 4.43 Fitted MGARCH for Morocco

Variable	Parameter	Estimate
MASI	ω	-0.2773 *
	α (1)	0.1202 ***
	δ (1)	0.9585 *
	γ	-0.177 ***
MAD	ω	0.0000
	α (1)	0.0413
	α (2)	0.1427 **
	δ (1)	0.0000
	δ (2)	0.7935 *
	ν - (Shape)	7.4838 ***
Gold	ω	-0.0692 *
	α (1)	-0.0109 *
	δ (1)	0.9896 *
	γ	-0.1203 *
	ν - (Shape)	12.6287 *
Oil	ω	0.0034 **
	α (1)	0.0000
	δ (1)	0.1811
	γ	0.4383
	ξ - (Skew)	0.7655 *
DCC	α_1	0.0000
	α_2	0.9591
	ν - (Joint Shape)	22.645

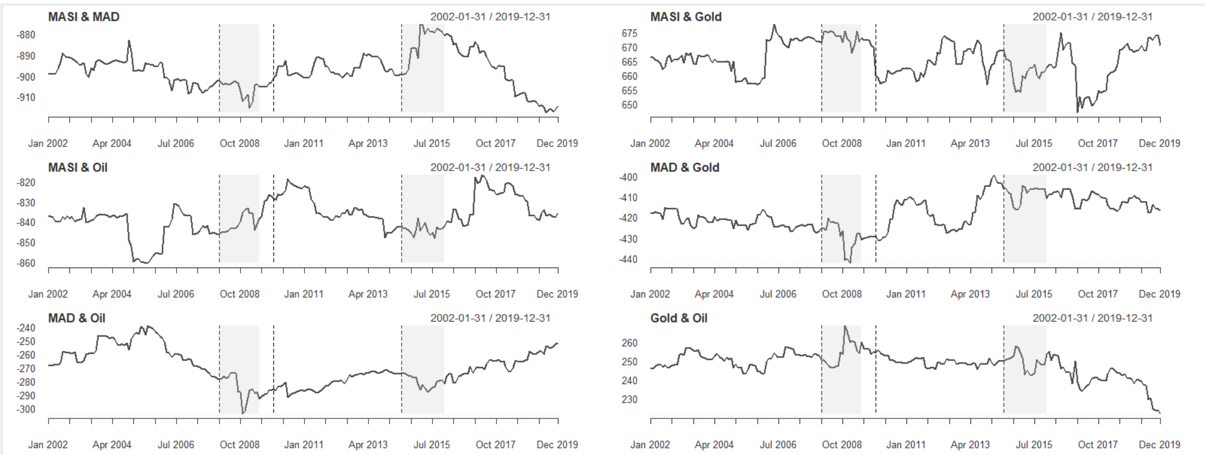

Figure 4.48 Morocco Dynamic Conditional Correlation

Table 4.44 Fitted MGARCH for Nigeria

Variable	Parameter	Estimate
NSE	ω	0.0008 *
	α (1)	0.011
	δ (1)	0.6914
	δ (2)	0.0000
	γ	0.2274
NGN	ω	0.0000
	α (1)	0.0000
	δ (1)	1 *
	γ	-0.129 *
Gold	ω	-0.0043
	α (1)	0.0606 *
	δ (1)	0.9999 *
	γ	-0.0219
	ν - (Shape)	14.1619
Oil	ω	0.0045 *
	α (1)	0.0000
	δ (1)	0.0345
	γ	0.5113
	ξ - (Skew)	0.715 *
DCC	α_1	0.0000
	α_2	0.9808 *
	ν - (Joint Shape)	20.9641 ***

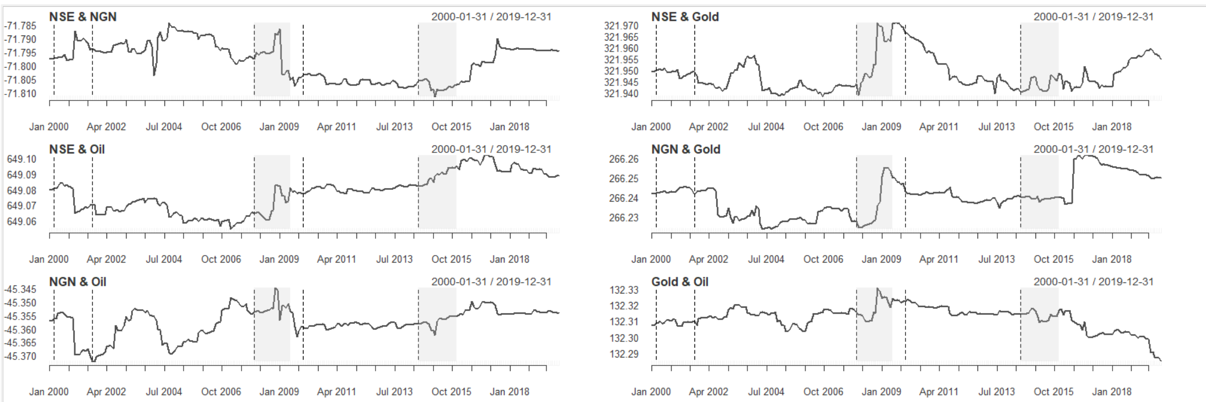

Figure 4.49 Nigeria Dynamic Conditional Correlation

Table 4.45 Fitted MGARCH for South Africa

Variable	Parameter	Estimate
SA ALSI	ω	0.0003
	α (1)	0.0469
	δ (1)	0.6232 **
	γ	0.423
ZAR	ω	0.0004 **
	α (1)	0.1352 ***
	δ (1)	0.6787 *
	ξ - (Skew)	1.2807 *
	ν - (Shape)	16.5262
Gold	ω	-0.0122 *
	α (1)	0.1074
	δ (1)	0.9999 *
	γ	-0.0912 *
	ν - (Shape)	13.258 **
Oil	ω	0.0021
	α (1)	0.0000
	δ (1)	0.4394
	γ	0.3615
	ξ - (Skew)	0.7047 *
DCC	α_1	0.0065
	α_2	0.9417 **
	ν - (Joint Shape)	18.8172

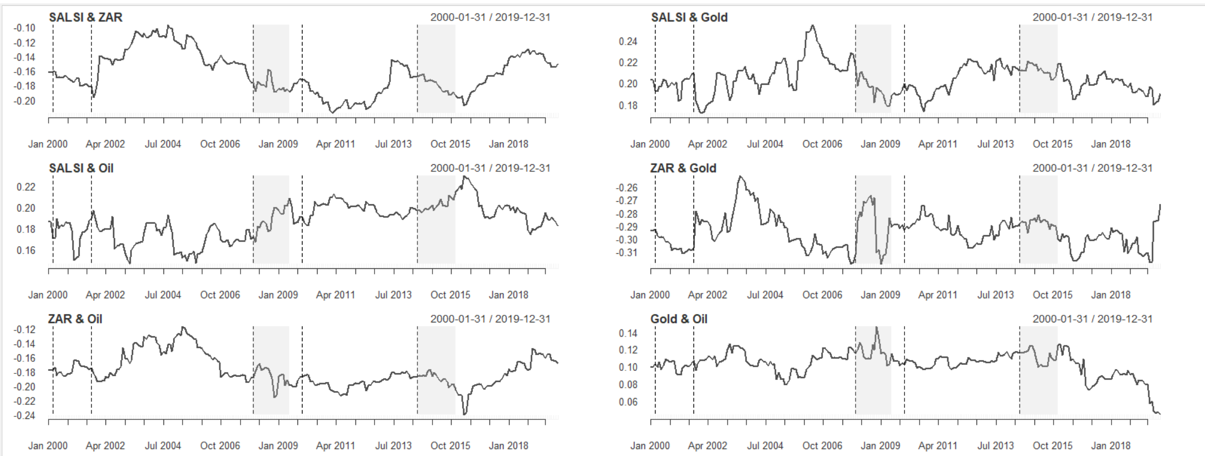

Figure 4.50 South Africa Dynamic Conditional Correlation

Table 4.46 Fitted MGARCH for Sudan

Variable	Parameter	Estimate
Khartoum 30	ω	0.0002
	α (1)	0.325
	δ (1)	0.674
	ν - (Shape)	2.8929 *
SDG	ω	0.0000
	α (1)	0.0000
	δ (1)	0.999 *
	ξ - (Skew)	1.3085 *
	ν - (Shape)	2.1543 *
Gold	ω	-1.9378
	α (1)	0.0211
	δ (1)	0.67 **
	γ	0.2439 ***
	ν - (Shape)	12.8854
Oil	ω	0.0004
	α (1)	0.2385 **
	δ (1)	0.6957 *
	γ	0.0632
	ξ - (Skew)	0.6931 *
DCC	α_1	0.0629 ***
	α_2	0.3903 ***
	ν - (Joint Shape)	50

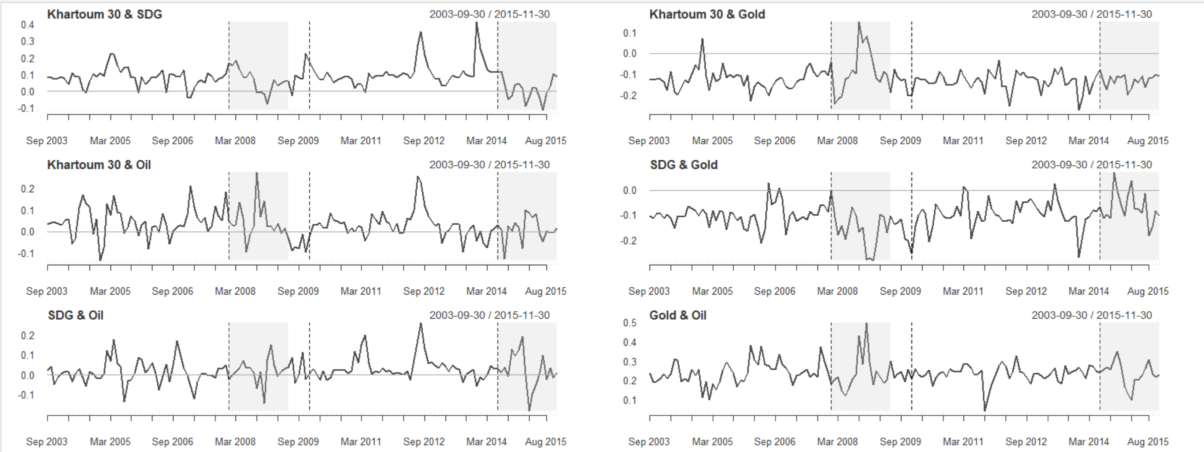

Figure 4.51 Sudan Dynamic Conditional Correlation

Table 4.47 Fitted MGARCH for Tanzania

Variable	Parameter	Estimate		Variable	Parameter	Estimate
DSEAI	Mean	0.0052 **		Gold	Mean	0.0043
	ω	0.0003			ar (1)	0.4861 *
	α (1)	0.74 ***			ma(1)	-0.5729 *
	δ (1)	0.259 **			ω	-0.9487
	ξ - (Skew)	1.2143 *			α (1)	0.0116
	ν - (Shape)	2.6109 *			δ (1)	0.841 *
TZS	Mean	0.0006 ***			γ	0.3339
	ar (1)	0.7474 *			ν - (Shape)	7.7586 ***
	ma(1)	-0.6666 *		Oil	Mean	0.009 ***
	ω	-0.2539			ar (1)	-0.0301
	α (1)	-0.8819 **			ω	0.0006 *
	δ (1)	0.9616 *			α (1)	0.0000
	γ	3.2577 *			δ (1)	0.7631 *
	ξ - (Skew)	1.0504 *			γ	0.169
	ν - (Shape)	2.01 *			ξ - (Skew)	1.5335 *
DCC	α_1	0.0578				
	α_2	0.9415 *				
	ν - (Joint Shape)	24.8498 **				

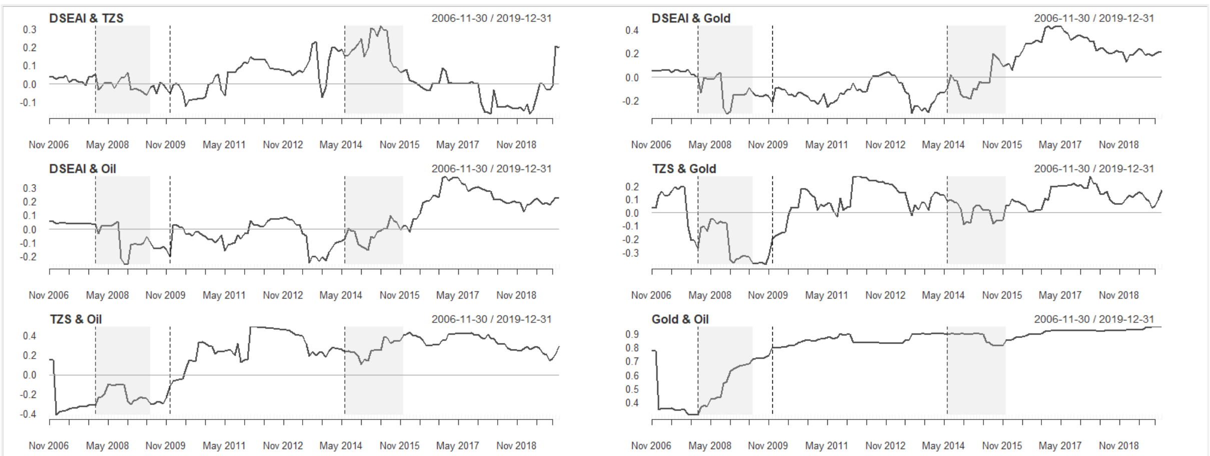

Figure 4.52 Tanzania Dynamic Conditional Correlation

Table 4.48 Fitted MGARCH for Tunisia

Variable	Parameter	Estimate
Tunindex	ω	-0.1181 *
	α (1)	0.0829 *
	δ (1)	0.9923 *
	δ (2)	-0.0091 *
	γ	-0.108 *
	ν - (Shape)	8.2639 *
TND	ω	0.0000
	α (1)	0.0644
	δ (1)	0.8669 *
	δ (2)	0.0000
	ν - (Shape)	8.0676 **
Gold	ω	-0.0162
	α (1)	0.1106
	δ (1)	0.9997 *
	γ	-0.1012
	ν - (Shape)	21.0424
Oil	ω	0.0039
	α (1)	0.0000
	δ (1)	0.1119
	γ	0.5215
	ξ - (Skew)	0.7288 *
DCC	α_1	0.0000
	α_2	0.0103
	ν - (Joint Shape)	20.0518

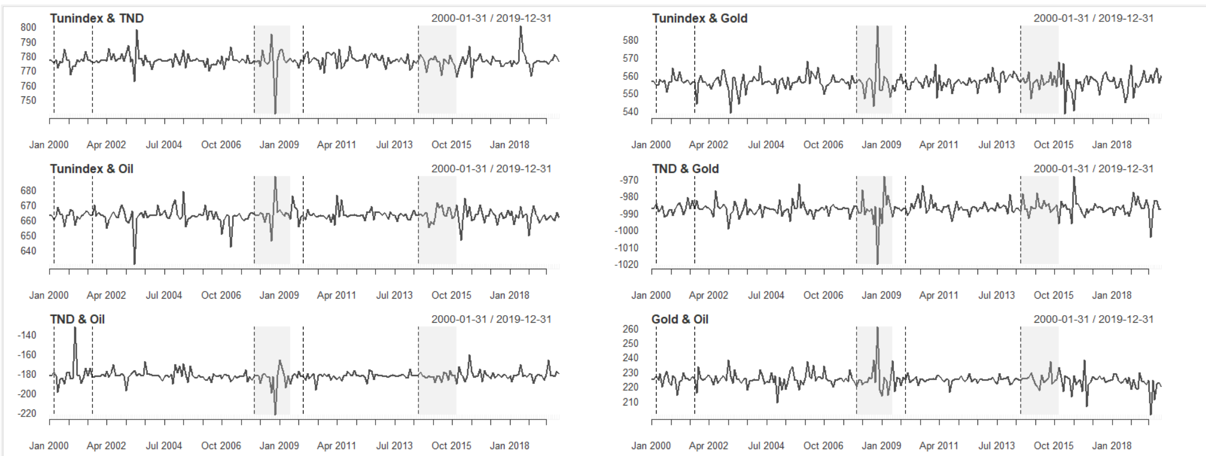

Figure 4.53 Tunisia Dynamic Conditional Correlation

Table 4.49 Fitted MGARCH for Uganda

Variable	Parameter	Estimate
UALSI	ω	0.0027
	α (1)	0.0000
	δ (1)	0.2158
	γ	0.6536
	ξ - (Skew)	0.715 *
UGX	ω	0.0001
	α (1)	0.3781 **
	δ (1)	0.6209 *
	ν - (Shape)	3.4101 *
Gold	ω	-0.8742
	α (1)	0.0394
	δ (1)	0.8545 *
	γ	0.2091
	ν - (Shape)	8.9448 ***
Oil	ω	0.0014 ***
	α (1)	0.1179
	δ (1)	0.5113 *
	γ	0.2787
	ξ - (Skew)	0.6789 *
DCC	α_1	0.0000
	α_2	0.9914 *
	ν - (Joint Shape)	28.6195

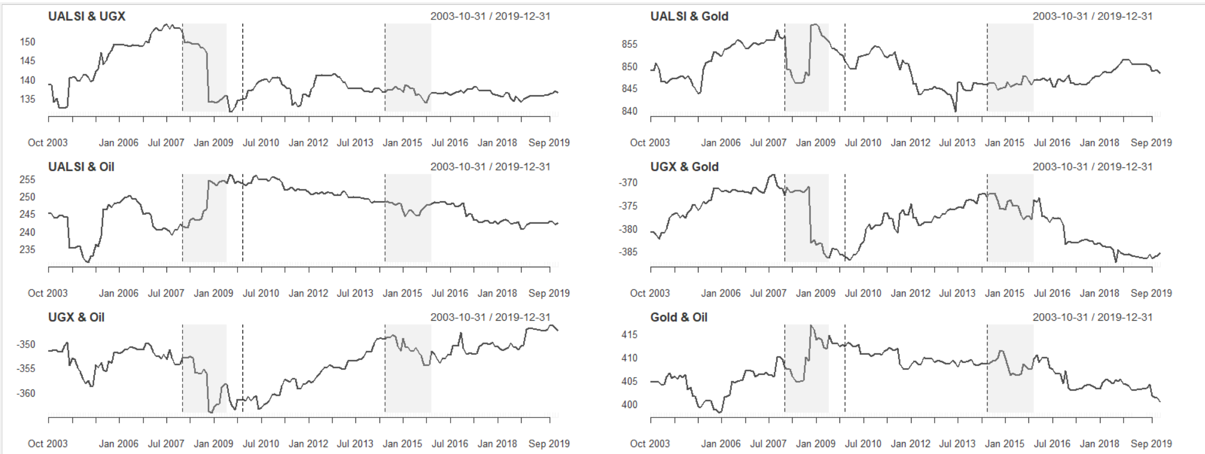

Figure 4.54 Uganda Dynamic Conditional Correlation

Table 4.50 Fitted MGARCH for Zambia

Variable	Parameter	Estimate
LuALSI	ω	-0.1144 *
	α (1)	-0.1358 *
	δ (1)	0.9802 *
	γ	-0.1793 *
	ν - (Shape)	4.1622 *
ZMK	ω	-0.2414 *
	α (1)	0.2823 *
	δ (1)	0.9626 *
	γ	-0.0108
	ξ - (Skew)	1.2415 *
	ν - (Shape)	3.9326 *
Gold	ω	-0.8275
	α (1)	-0.0302
	δ (1)	0.8647 *
	γ	0.276
	ν - (Shape)	10.5737
Oil	ω	0.001
	α (1)	0.0000
	δ (1)	0.6061
	γ	0.4394
	ξ - (Skew)	0.6447 ***
DCC	α_1	0.0086
	α_2	0.9117 *
	ν - (Joint Shape)	29.6786

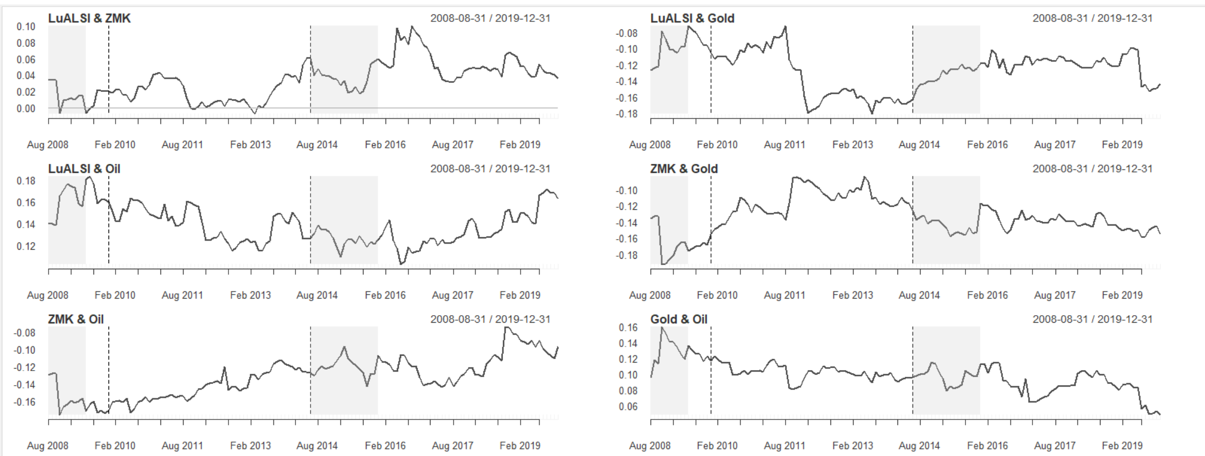

Figure 4.55 Zambia Dynamic Conditional Correlation

4.3.5 Dynamic Association amongst Currency Markets

The models fitted in section 4.3.4 indicate that there is a dynamic dependence that exist for each economy intra-markets. A question that arise is that of the potential dependence relationship that would exist amongst markets of African economies that would likely be a result of a spill-over amongst markets. Due to stock markets' data availability the dependence relationship inter economies is modelled in this section for the exchange rates markets of the sampled economies.

Table 4.51 Fitted MGARCH for All Currencies

Variable	Parameter	Estimate
DZD	ω	-2.049 *
	α (1)	-0.0917
	δ (1)	0.7521 *
	γ	0.5716 *
	ξ - (Skew)	1.206 *
	ν - (Shape)	3.0119 *
AOA	ω	0.0004 ***
	α (1)	0.99999 ***
	δ (1)	0.2825 ***
	γ	-0.7078
	ν - (Shape)	2.5355 *
BWP	ω	0.0000
	δ (1)	0.9982 *
	ξ - (Skew)	1.1176 *
	ν - (Shape)	7.6405 **
XOF	ω	-0.9867
	α (1)	0.0925
	δ (1)	0.8636 *
	γ	0.2381 *
	ξ - (Skew)	1.0589 *
	ν - (Shape)	12.8621
CDF	ω	0.0015
	α (1)	0.2546
	δ (1)	0.5863 **
	γ	-0.0449
	ν - (Shape)	2.5133 *
EGP	ω	-1.1669 ***
	α (1)	-0.4339
	δ (1)	0.7407 *
	γ	0.996 ***
	ξ - (Skew)	1.474 *
	ν - (Shape)	2.0219 *

Variable	Parameter	Estimate
ETB	ω	-0.0883 *
	α (1)	0.0326 *
	δ (1)	0.9875 *
	γ	-0.2592 *
	ξ - (Skew)	1.5648 *
	ν - (Shape)	2.0929 *
GHS	ω	0.0001
	α (1)	0.6126
	δ (1)	0.6019 *
	γ	-0.3958
	ξ - (Skew)	1.6411 *
	ν - (Shape)	3.5612 **
KES	ω	0.0000
	α (1)	0.2958 **
	δ (1)	0.6898 *
	ν - (Shape)	3.6837 *
LYD	ω	0.0000
	α (1)	0.0000
	δ (1)	0.963 *
	ν - (Shape)	3.8018 *
MAD	ω	0.0000
	α (1)	0.049
	α (2)	0.1194
	δ (1)	0
	δ (2)	0.8129
	ν - (Shape)	7.6781
NGN	ω	0.0000
	α (1)	0.223 *
	δ (1)	0.6214 *
	γ	0.1066 *

Table 4.52 Continuation of Fitted MGARCH for All Currencies

Variable	Parameter	Estimate
ZAR	ω	0.0004 ***
	α (1)	0.1295 ***
	δ (1)	0.7056 *
	ξ - (Skew)	1.2492 *
	ν - (Shape)	9.6334 ***
SDG	ω	0.0125 **
	α (1)	0.1357
	δ (1)	0.7608 *
	ξ - (Skew)	1.4851 *
	ν - (Shape)	2.022 *
TZS	ω	-0.7376 *
	α (1)	-0.2627
	δ (1)	0.9022 *
	γ	0.8763 **
	ξ - (Skew)	1.3253 *
	ν - (Shape)	2.2989 *
TND	ω	0.0000
	α (1)	0.0611 ***
	δ (1)	0.8754 *
	δ (2)	0.0000
	ν - (Shape)	6.9052 **
UGX	ω	0.00004 ***
	α (1)	0.3456 *
	δ (1)	0.6534 *
	ν - (Shape)	3.7702 *
ZMK	ω	-1.5652
	α (1)	0.222
	δ (1)	0.7297 *
	γ	0.5125 **
	ξ - (Skew)	1.0622 *
	ν - (Shape)	2.8083 *
DCC	α_1	0.0011
	α_2	0.7237 *
	ν - (Joint Shape)	50 *

Table 4.53 Currency Average Dynamic Correlation

Variable	DZD	AOA	BWP	XOF	CDF	EGP	ETB	GHS	KES	LYD	MAD	NGN	ZAR	SDG	TZS	TND	UGX	ZMK
DZD	-	-13%	37%	52%	1%	-1%	-2%	-6%	15%	28%	51%	-10%	33%	4%	14%	49%	19%	11%
AOA	-13%	-	-4%	-12%	9%	3%	-6%	6%	1%	-2%	-10%	9%	3%	9%	-4%	-11%	3%	12%
BWP	37%	-4%	-	54%	1%	10%	2%	5%	26%	29%	51%	-1%	93%	2%	22%	49%	14%	16%
XOF	52%	-12%	54%	-	-1%	2%	0%	8%	27%	59%	97%	-2%	46%	6%	13%	87%	19%	12%
CDF	1%	9%	1%	-1%	-	5%	-1%	4%	7%	2%	2%	9%	2%	5%	-1%	1%	9%	16%
EGP	-1%	3%	10%	2%	5%	-	-10%	-6%	18%	6%	3%	-3%	9%	8%	12%	9%	18%	15%
ETB	-2%	-6%	2%	0%	-1%	-10%	-	6%	-3%	-9%	1%	3%	2%	7%	-1%	-1%	-5%	1%
GHS	-6%	6%	5%	8%	4%	-6%	6%	-	9%	5%	6%	14%	3%	-2%	-2%	5%	-8%	18%
KES	15%	1%	26%	27%	7%	18%	-3%	9%	-	19%	26%	3%	26%	7%	26%	26%	32%	16%
LYD	28%	-2%	29%	59%	2%	6%	-9%	5%	19%	-	59%	4%	24%	-15%	14%	54%	12%	8%
MAD	51%	-10%	51%	97%	2%	3%	1%	6%	26%	59%	-	2%	44%	6%	16%	83%	19%	15%
NGN	-10%	9%	-1%	-2%	9%	-3%	3%	14%	3%	4%	2%	-	-1%	-6%	3%	-1%	-3%	18%
ZAR	33%	3%	93%	46%	2%	9%	2%	3%	26%	24%	44%	-1%	-	3%	20%	41%	16%	18%
SDG	4%	9%	2%	6%	5%	8%	7%	-2%	7%	-15%	6%	-6%	3%	-	-2%	9%	9%	-6%
TZS	14%	-4%	22%	13%	-1%	12%	-1%	-2%	26%	14%	16%	3%	20%	-2%	-	16%	22%	6%
TND	49%	-11%	49%	87%	1%	9%	-1%	5%	26%	54%	83%	-1%	41%	9%	16%	-	22%	13%
UGX	19%	3%	14%	19%	9%	18%	-5%	-8%	32%	12%	19%	-3%	16%	9%	22%	22%	-	16%
ZMK	11%	12%	16%	12%	16%	15%	1%	18%	16%	8%	15%	18%	18%	-6%	6%	13%	16%	-

Table 4.54 Currency Average Kendall Tau

Variable	DZD	AOA	BWP	XOF	CDF	EGP	ETB	GHS	KES	LYD	MAD	NGN	ZAR	SDG	TZS	TND	UGX	ZMK
DZD	-	-8%	24%	35%	1%	0%	-1%	-4%	10%	18%	34%	-6%	21%	2%	9%	33%	12%	7%
AOA	-8%	-	-3%	-7%	6%	2%	-4%	4%	1%	-1%	-6%	6%	2%	6%	-2%	-7%	2%	8%
BWP	24%	-3%	-	36%	0%	6%	1%	3%	17%	19%	34%	-1%	76%	2%	14%	33%	9%	10%
XOF	35%	-7%	36%	-	-1%	2%	0%	5%	17%	40%	83%	-1%	30%	4%	8%	67%	12%	8%
CDF	1%	6%	0%	-1%	-	3%	-1%	2%	5%	1%	1%	6%	1%	3%	0%	1%	6%	10%
EGP	0%	2%	6%	2%	3%	-	-7%	-4%	11%	4%	2%	-2%	6%	5%	8%	6%	11%	9%
ETB	-1%	-4%	1%	0%	-1%	-7%	-	4%	-2%	-6%	1%	2%	1%	5%	-1%	-1%	-3%	1%
GHS	-4%	4%	3%	5%	2%	-4%	4%	-	6%	3%	4%	9%	2%	-1%	-1%	3%	-5%	12%
KES	10%	1%	17%	17%	5%	11%	-2%	6%	-	12%	17%	2%	17%	4%	17%	17%	21%	10%
LYD	18%	-1%	19%	40%	1%	4%	-6%	3%	12%	-	40%	3%	16%	-9%	9%	36%	8%	5%
MAD	34%	-6%	34%	83%	1%	2%	1%	4%	17%	40%	-	1%	29%	4%	10%	63%	12%	10%
NGN	-6%	6%	-1%	-1%	6%	-2%	2%	9%	2%	3%	1%	-	0%	-4%	2%	-1%	-2%	12%
ZAR	21%	2%	76%	30%	1%	6%	1%	2%	17%	16%	29%	0%	-	2%	13%	27%	10%	11%
SDG	2%	6%	2%	4%	3%	5%	5%	-1%	4%	-9%	4%	-4%	2%	-	-1%	6%	6%	-4%
TZS	9%	-2%	14%	8%	0%	8%	-1%	-1%	17%	9%	10%	2%	13%	-1%	-	10%	14%	4%
TND	33%	-7%	33%	67%	1%	6%	-1%	3%	17%	36%	63%	-1%	27%	6%	10%	-	14%	9%
UGX	12%	2%	9%	12%	6%	11%	-3%	-5%	21%	8%	12%	-2%	10%	6%	14%	14%	-	10%
ZMK	7%	8%	10%	8%	10%	9%	1%	12%	10%	5%	10%	12%	11%	-4%	4%	9%	10%	-

Table 4.53 and Table 4.54 show the average association measures (amongst currencies) that are derived from the t-copula DCC model whose parameter estimations are shown in Table 4.51 and Table 4.52. The tables show varying levels of association amongst major African currencies, such as the high and low absolute dependence measured between MAD and XOF and ETB and XOF, $\rho_\tau = 0.834$ and $\rho_\tau = 0.001$, respectively. Currencies of economies such as Algeria (DZD), Botswana (BWP), Libya (LYD), Morocco (MAD), South Africa (ZAR), Tunisia (TND) and the regional XOF have a high absolute association amongst themselves and other economies. For instance, the TND shows a high bivariate association to the DZD, BWP, XOF, LYD, MAD and ZAR. The high association amongst currencies of these economies could be a result of a trade agreements channel that results in a level of ease at which trade can flow and this can be observed by their inclusion in most African regional economic communities. The association also means that economically the change in the currencies have a common driver such as the change in the price of commonly traded goods and exported commodities. In the figures below the dynamic relationship amongst only these currencies is presented over the sample period. This is in line with the common depreciation that was observable in the upward trend at price level data. Each figure shows a consistent co-movement amongst currencies that revolves around the average measure. For most economies the trend is sustained but there is a visual perturbation that seems to occur in and around the highlighted crises periods. For economies such as those with high stable associations, the external influence on the economy could be an example of none-systematic risk imposed by the relationship the economy's functions have with external and trading partners such as terms of trade.

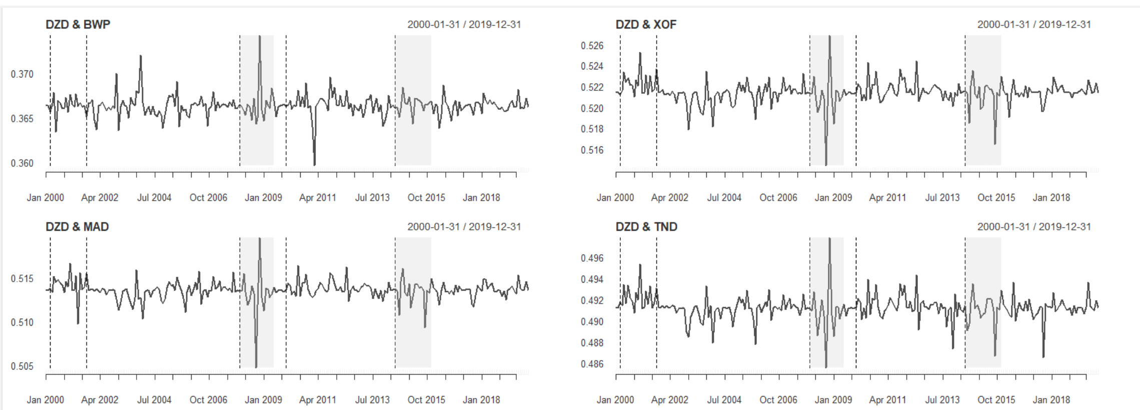

Figure 4.56 Dynamic Conditional Correlation of DZD, BWP, XOF, MAD and TND

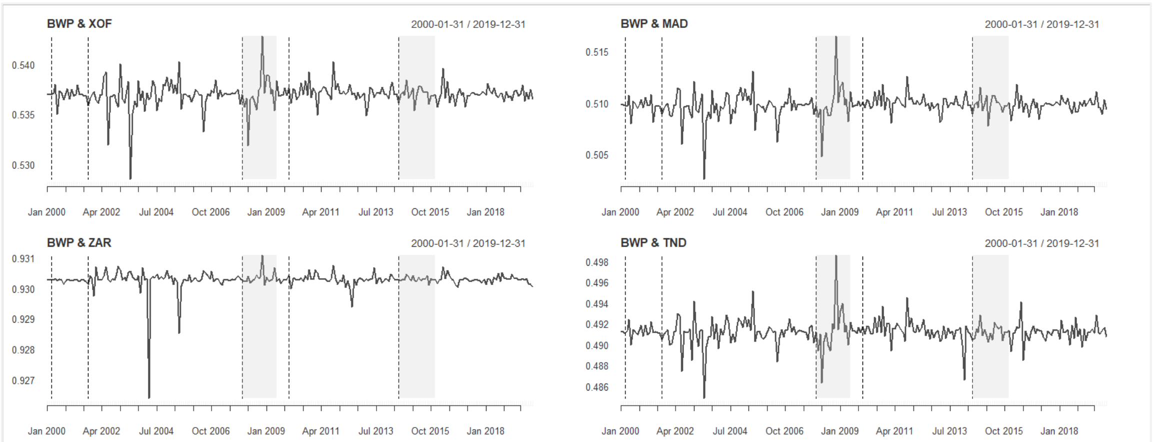

Figure 4.57 Dynamic Conditional Correlation of BWP, XOF, MAD, ZAR and TND

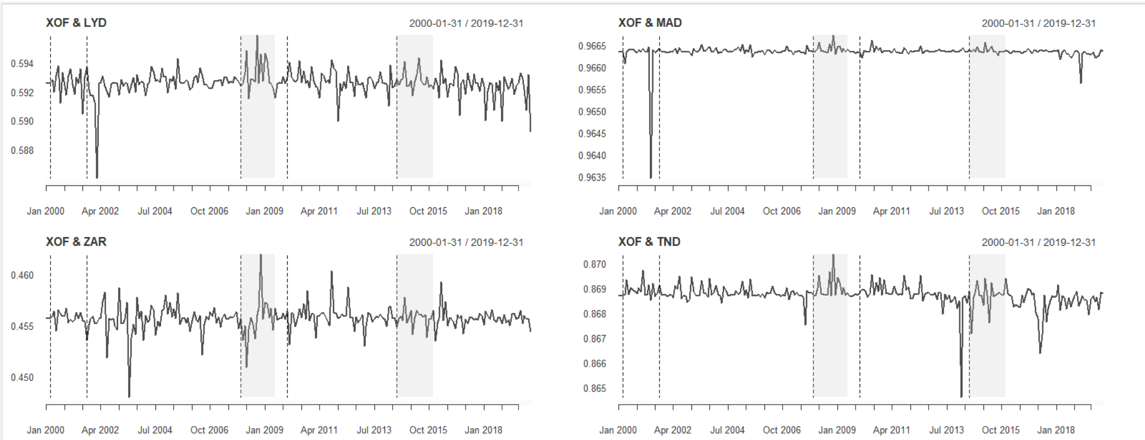

Figure 4.58 Dynamic Conditional Correlation of XOF, LYD, MAD, ZAR and TND

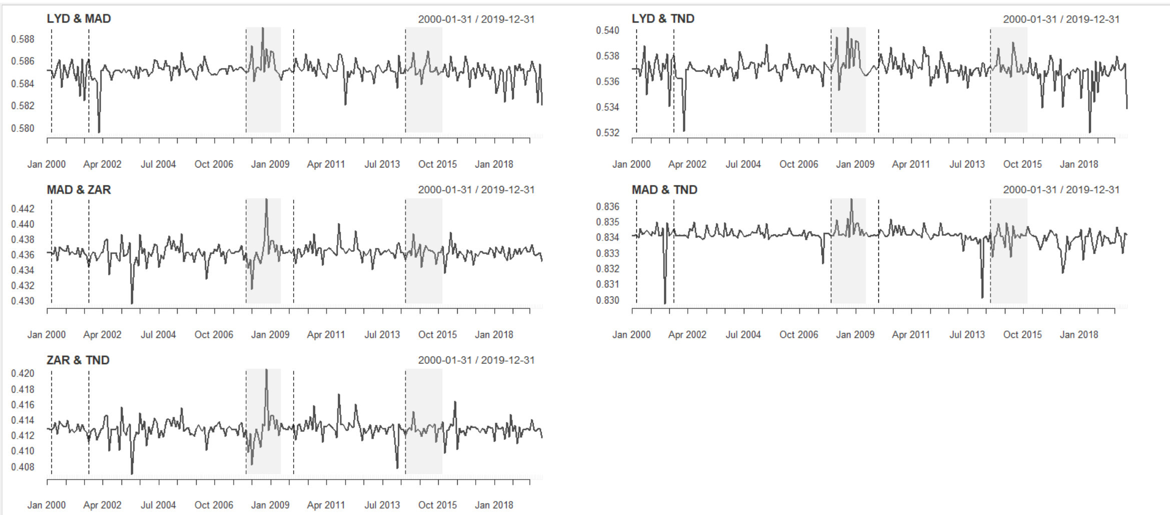

Figure 4.59 Dynamic Conditional Correlation of LYD, MAD, ZAR and TND

4.3.6 Dynamic Association amongst Specific Stock and Currency Markets

The high levels of bivariate dependence shown between the currencies ZAR and BWP; MAD and XOF; MAD and TND; and XOF and TND show potential properties of either the "flow-oriented" and "stock-oriented" models that suggest a significant information movement between stock and currency markets. A model is fitted and estimated using only currency and stock market data points of the four economies (excluding the regional XOF and BRVMCI, due to the BRVMCI data availability) to assess the possibility of co-movements.

Table 4.55 Fitted MGARCH for Botswana, Morocco, South Africa and Tunisia

Variable	Parameter	Estimate	Variable	Parameter	Estimate
BWP	ω	0.0000	BSEDCI	ω	0.00004 ***
	δ (1)	0.9985 *		α (1)	0.2158 ***
	ξ - (Skew)	1.22 *		δ (1)	0.7507 *
	ν - (Shape)	10.4206		ν - (Shape)	4.6656 *
MAD	ω	0.00001	MASI	ω	-0.21
	α (1)	0.0056		α (1)	0.067
	α (2)	0.1414 ***		δ (1)	0.9658 *
	δ (1)	0.3344		γ	0.1326
	δ (2)	0.4935			
	ν - (Shape)	10.2368			
ZAR	ω	0.0004 ***	SALSI	ω	0.0003
	α (1)	0.1626 **		α (1)	0.0756
	δ (1)	0.6667 *		δ (1)	0.6361 *
	ξ - (Skew)	1.3496 *		γ	0.3462
	ν - (Shape)	34.3052			
TND	ω	0.0000	Tunindex	ω	-1.554 **
	α (1)	0.0502		α (1)	0.0747
	δ (1)	0.8897 *		δ (1)	0.9999
	δ (2)	0		δ (2)	-0.2275
	ν - (Shape)	7.1242 **		γ	0.3053 ***
				ν - (Shape)	6.4961 **
DCC	α_1	0.0121 ***			
	α_2	0.9326 *			
	ν - (Joint Shape)	27.2896 *			

Table 4.56 Sampled Markets' Average Dynamic Correlation

Variable	BWP	MAD	ZAR	TND	SALSI	Tunindex	MASI	BSEDCI
BWP	-	50%	92%	48%	-15%	-6%	-11%	11%
MAD	50%	-	43%	83%	-26%	2%	-3%	3%
ZAR	92%	43%	-	41%	-16%	-8%	-17%	9%
TND	48%	83%	41%	-	-23%	1%	-5%	2%
SALSI	-15%	-26%	-16%	-23%	-	1%	18%	5%
Tunindex	-6%	2%	-8%	1%	1%	-	6%	2%
MASI	-11%	-3%	-17%	-5%	18%	6%	-	1%
BSEDCI	11%	3%	9%	2%	5%	2%	1%	-

Table 4.57 Sampled Markets' Average Kendall Tau

Variable	BWP	MAD	ZAR	TND	SALSI	Tunindex	MASI	BSEDCI
BWP	-	33%	75%	32%	-9%	-4%	-7%	7%
MAD	33%	-	28%	63%	-17%	1%	-2%	2%
ZAR	75%	28%	-	27%	-10%	-5%	-11%	6%
TND	32%	63%	27%	-	-14%	1%	-3%	2%
SALSI	-9%	-17%	-10%	-14%	-	0%	11%	3%
Tunindex	-4%	1%	-5%	1%	0%	-	4%	1%
MASI	-7%	-2%	-11%	-3%	11%	4%	-	0%
BSEDCI	7%	2%	6%	2%	3%	1%	0%	-

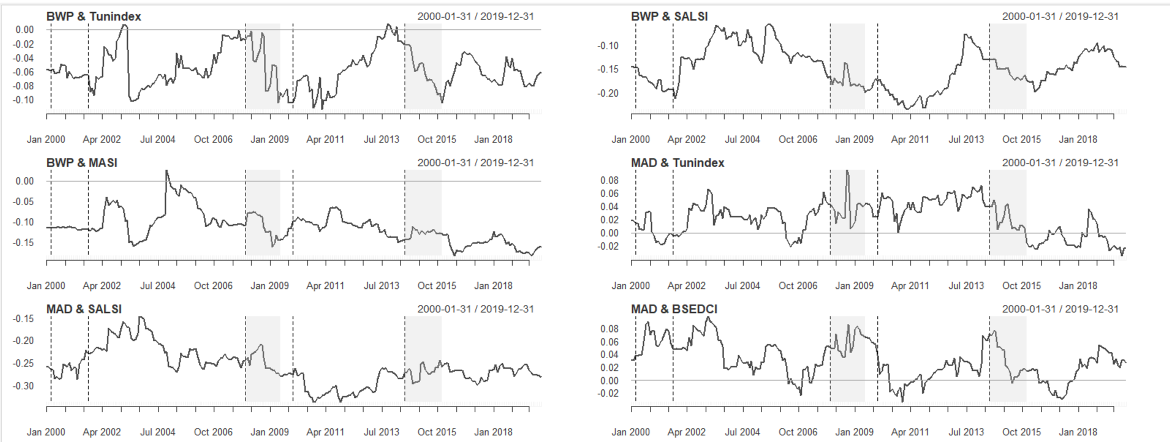

Figure 4.60 Dynamic Conditional Correlation of BWP, MAD and Stock market indices BSEDCI, SALSI, MASI and Tunindex

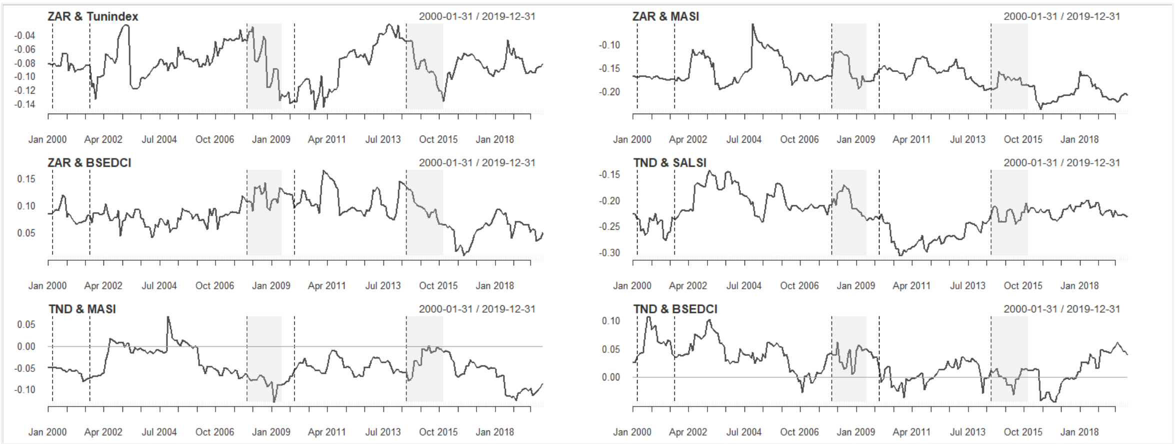

Figure 4.61 Dynamic Conditional Correlation of ZAR, TND and Stock market indices BSEDCI, SALSI, MASI and Tunindex

The high levels of bivariate dependence shown amongst the currencies do not necessarily mean for this case transmission to the stock market of an economy. This can be seen by the low levels of association that are observed between exchange rates and stock market indices of other economies. Depicted in Figure 4.60 and Figure 4.61 above are association values that are on average below 17% between stock markets and currency markets showing not enough evidence to conclude that a change in the price of an African currency can influence or shock it domestic and external stock market, other factors held constant. The none exitance of evidence for domestic influence between stock and exchange rates markets can be seen in the low dependence measures shown in Table 4.31 and Table 4.32. The low measures could be caused by other latent or none-sampled variables that are pertinent drivers of change in African stock market prices or activity such as economic activity of major trading partners.

4.3.7 Goodness of Fit for DCC GARCH

To check each fitted model's adequacy, a Ljung–Box portmanteau test is performed on the standardized residuals and squared standardized residuals of each model to ensure that there is not any form of serial correlation, volatility clustering or heteroscedasticity and the results are reported in Table 4.58. Hosking (1980) proposes a multivariate version of the portmanteau test that is applied on the standardized residuals and reported as a dependogram for each economy's fitted copula based DCC GARCH model. The multivariate version of the arch LM and portmanteau test is applied on the standardized residuals and squared standardized residuals, respectively. For the portmanteau test performed on squared residuals there are two set of p-values reported, where one set is made up of the usual ARCH LM test p-value the second set is from the results of a robust multivariate ARCH LM test. The robust test eliminates the possibility of the portmanteau test being impacted by the tail behaviour of the tested residuals and this is done by trimming-out data that is outside the 95th percentile data range (Tsay, 2014). From the results reported in Table 4.58, there is not enough evidence of remaining heteroscedasticity nor volatility clustering post fitting the DCC GARCH model except for when using a t – copula DCC to jointly fit the DRC's variables. Using squared standardised residuals, robust results show that there is a potential of non-constant tail behaviour from the data. This tail related observation is due to the varying p-value results from the portmanteau test performed on the 95th percentile range to those from the overall data. The overall GOF fit results of the copula DCC are quite similar regardless of the copula being applied in the model for most economies.

Table 4.58 GOF Copula DCC GARCH

Economy/Model	ARCH LM Test		Res. ^ 2		Res. ^ 2 (Robust)	
	t	***N***	***t***	***N***	***t***	***N***
Algeria	0.8245	0.8246	0.9999	0.9999	0.7104	0.7062
Angola	0.9990	0.9990	0.7047	0.7058	0.8837	0.8826
Botswana	0.8658	0.8658	0.9777	0.9777	0.2963	0.2967
DRC	1.0000	1.0000	0.4051	0.4348	0.9635	0.7820
Cote d'Ivoire	0.6313	0.6314	0.9570	0.9572	0.9505	0.9505
Arab Rep. of Egypt	1.0000	1.0000	0.9722	0.9702	0.2265	0.2182
Ethiopia	0.9270	0.9269	0.9569	0.9567	0.9047	0.9031
Ghana	0.6975	0.6975	0.8604	0.8611	0.9688	0.9690
Kenya	0.1909	0.2179	0.8469	0.8642	0.9220	0.8345
Libya	1.0000	1.0000	0.0320	0.0320	0.8476	0.8356
Morocco	0.2803	0.2801	0.1237	0.1224	0.8454	0.8471
Nigeria	0.9189	0.9190	0.9995	0.9994	0.0784	0.0765
South Africa	0.1673	0.1669	0.0505	0.0512	0.3671	0.3701
Sudan	0.9967	0.9967	0.7137	0.7176	0.6643	0.6630
Tanzania	1.0000	1.0000	1.0000	1.0000	0.6788	0.6040
Tunisia	0.3813	0.3816	0.7969	0.8036	0.7105	0.7091
Uganda	0.9317	0.9317	1.0000	1.0000	0.8450	0.8392
Zambia	0.5269	0.5255	0.9987	0.9987	0.2787	0.2798
Currencies	0.3847	0.1669	0.9783	0.0512	0.2321	0.3701
Equities	0.1335	0.2577	0.2014	0.3718	0.4922	0.6285

The ensuing step offers a view on the dependograms derived from the copula based DCC model. Each dependogram shows a p-value (depicted as “prob”) that is a result from the portmanteau test that is applied on the first 15 lags (depicted as “m”) of the model’s standardised residual. Due to the similarity of t and Normal copula the visuals, only one is shown per economy in Figure 4.62 and Chapter 1Appendix C. . The models fitted for each economy show no evidence of serial correlation relationship amongst the standardised residuals.

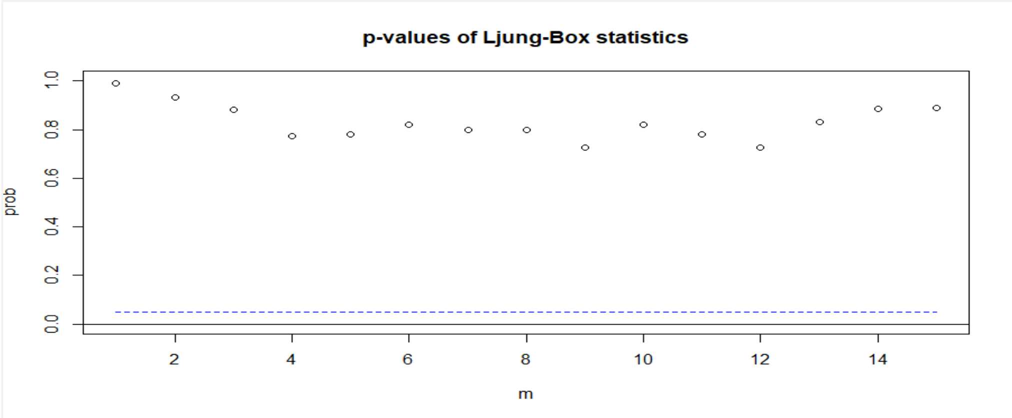

Figure 4.62 Algeria Ljung–Box Dependogram

4.4 Causality

Causality is the ability of improving the prediction error by the inclusion of a variable in the prediction of another. In this case, a conditional multivariate Granger-causality test would be based on the existence of prediction error improvement in the conditional inclusion of a statistically significant variable. The causality test could be performed in the mean and in the volatility of models. The mean model causality test performed in this subsection would be based on the vector autoregressive like model fitted on the data per economy. The obvious limitations of this test are based on volatility having been shown in the previous sections, 4.3.3 and 4.3.4, to be a significant factor in modelling the sampled data. Hence relations beyond those captured by a constant variance type of model exist amongst the sample data and that causal inferences from a such model could be insufficient. Hence, with the limitations of the causality in the such tests, only the causality in volatility tests are considered. Using the argument by Chang and Mcaleer (2017) causality for this specific case can be derived from the significance of the elements in the "GARCH" and "ARCH" vectors in the multivariate GARCH models fitted in the section 4.3.4.

Representing volatility structure similar to Engle and Kroner (1995), in a BEKK-GARCH model, also allows one to study the magnitudes of the volatility spill overs amongst variables. Jin, Xiaowen Lin and Tamvakis (2012) use a VAR-BEKK and visualise volatility impulse response functions that show how a shock induced to a variable affects other variables in the system. Using R's (variance impulse response functions) VIRF package, the visual in Figure 4.63 (and the figures in Chapter 1Appendix D.) use a similar approach to show how causality can also be inferenced when a system is shocked at a point. The results continue to show the relationship amongst variables that is shown in the recent section. For example, the negative relationship shown for the model of Algeria can be visualised when a shock at t=1 to DZAIR has a visual impulse positive reaction to DZD at t=10.

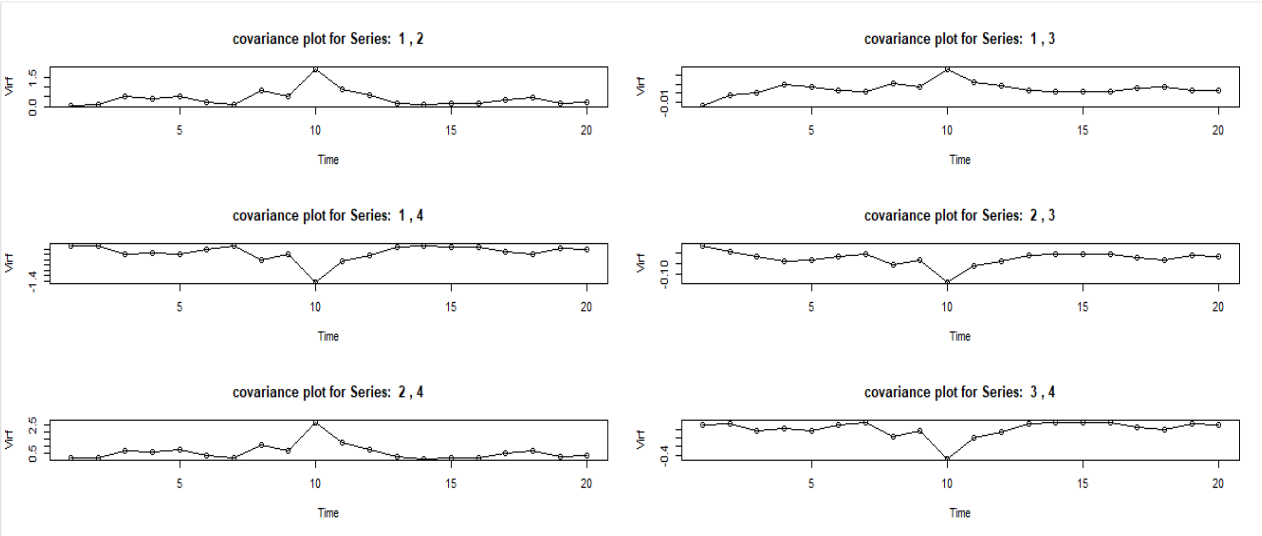

Figure 4.63 Algeria VIRF (Series order: DZAIR, DZD, Gold and Oil)

4.5 Chapter Summary

This section of the dissertation initially presented a return perspective analysis and basic statistics that showed that the returns data points have stylised facts such as non-normality, skewedness and are also leptokurtic. Secondly, assessed and found linear association between each variable’s current and lagged values. Thirdly, showed the non-constant correlation on a bivariate returns level. After showing the data to be non-normal and weakly stationary, the chapter further dealt with assessing the relationship of the sampled variables by including past volatility and this is due to volatility behaviour such as clustering being attributable to the observed relation in the returns of some sampled variables.

In the secondary parts of the chapter, conditional volatility was measured by a GARCH process and its dependence structure explained by a copula. The multivariate GARCH models fitted in this section have extended the knowledge that was available from analysing the cross correlation of the variables from a return perspective. The volatility structure of the univariates and multivariate show the existence of non-constant variance that is impacted by its past values that should be considered for each variable beyond its unconditional structure. The dependence in the volatility amongst the sampled assets highlighted a non-uniform relationship that has a level of congruence and variation with findings from previous studies. For instance, there is consistency in part with the findings of a negative relationship between currencies and crude oil with the research of Mollick and Sakaki (2019) who study the relationship of crude oil and 14 currencies; that of Zankawah and Stewart (2019) who studied the impact of oil prices to the Ghanaian cedi. There is also a finding of positive dependence association between the volatility of crude oil and gold that is in most of the fitted models that is also presented in the research by Jain and Biswal (2016) and Bedoui et al (2018). The models fitted for the majority of the sampled economies show a negative relationship between currencies and gold which is line with the results of Baur and McDermott (2016). The research by Nguyen et al. (2016); Raza et al. (2016) and Adewuyi, Awodumi and Abodunde (2019) also show that amongst the sampled economies' stock market indices there were varying results including those of economies whose stock market dependence with gold was not negative and this was true for Indonesia, Japan, Philippine and South Africa. The results presented are also in agreement with the impact between the foreign currencies and equities highlighted by Fowowe (2015); Blau (2018) and Ahmed and Huo (2020) for economies such as China, Côte d'Ivoire, Egypt, Nigeria and Kenya.

Though the none-constant DCC GARCH volatility model is a better fit of the data, there are economies onto which a constant multivariate volatility structure, such as the CCC GARCH, would be able to fit the models due to the small change in volatility over time. However, from plotting or visualising the conditional correlation, the none changing volatility would limit the ability to show the dynamic change in correlation (and covariation) process over time. For instance, though the conditional correlation change observed for economies such as Algeria and Angola are small and revolve around the average for the period, that observed for South Africa, Egypt and Zambia are relatively larger. In all the correlation charts the grey area showing a one and a half years post crisis view has been added for the two global crises, the 2008 financial crisis and 2014 oil price plunge. This highlighted area generally shows a change in the relationship observed between variables and could mean that during periods of market turmoil both policy makers and market participants should expect a shift in the relationship. This dynamic nature in the relationship amongst variables such as stock markets and crude oil is also emphasised by Xu et al. (2019).The final section of this chapter further presented a discussion on informational flow and visualised how a shock in a variable at time t can likely results in an impulse response at a later period. The impulse assist in further understanding the relationship amongst the variables.

5 Conclusion

The extractive industry in the continent of Africa is dominated by a global commodities market in which constituents' economies partake as consumers and producers. For producers, revenues from this industry are used as a source to finance economic activity while for consumers it becomes an expenditure burdening economic agents. Hence, fluctuation of prices in this industry results in potential challenges and advantages due to factors such as elasticity and (import and export) diversification. In this study, the association of change amongst the prices of commodities (where gold and oil are used as proxies), equities and currency markets are researched and were found using a multivariate volatility perspective of the copula extension of the DCC GARCH. The study sampled African economies of Algeria, Angola, Botswana, Democratic Republic of Congo, Côte d'Ivoire, Arab Rep. of Egypt, Ethiopia, Ghana, Kenya, Libya, Morocco, Nigeria, South Africa, Sudan, Tanzania, Tunisia, Uganda and Zambia. These economies over the sampled period of 2000 – 2019, were significantly contributing to the GDP of the continent. Due to some countries being members of an economical union that has a regional stock market and currency, only a representative country was chosen, and this was the case for Cameroon and Gabon being represented by Côte d'Ivoire. The measure of dependence emanating from price fluctuations is found to be time varying for economies but observed to be relatively high for the economies of Egypt, South Africa, Tanzania, Libya and Zambia while it evolves at a scale around the average measured association for other economies and this observation was made without any separation based on net-export status. The results show that over the sampled period, movements in the commodities market has influenced varying change in the financial markets which is represented the by currency and stock markets. This factor could mean that, future studies with a focus on African economies should keep abreast of and by understanding the impact from other possibly linked markets such as the commodities market. The association amongst currencies for the sampled economies also show time varying bivariate dependence that is relatively higher for the economies of Botswana, Côte d'Ivoire, Morocco, South Africa and Tunisia. The quantitatively high association for these economies' foreign exchange can be attributed to their geographical location, exchange rate systems in use during the sample period, similarities to export and import sector and membership in particular economic zones. All the sampled currencies also show a low co-movement association relationship with domestic (and foreign) stock markets. Conditional causality is also investigated and is considered as implied by the inclusion of the significant historical volatility of a variable in the multivariate models. The study finds proof of leverage effect in the univariate time series of most variables that indicate the asymmetric impact of positive and negative shocks. The study also finds that both oil and gold show haven or hedge properties for the dollar denominated currencies of the sampled economies due to their observed consistent negative association relationship within the study period. However, the negative dependence means that local currency units' volatility and returns are likely to positively co-move with the commodity prices. This study has established levels of dependence but does not delve and investigate deeper into finding the actual causes of the dependence such as possible common costs and usage behaviour of sampled variables in certain dominant economic industries.

As economies continue to evolve technologically, past trading impediments are being resolved and barriers removed allowing for markets to interact regardless of geographic location. Hence, the need to further study African markets' dependencies by economic agents such as; policy makers, regulators, risk averse portfolio managers and investors, for reasons such as assessing risks and benefits of existing agreements in areas including risk aggregation, trading, production, supply chain and investment. Such studies could further look for insights on the potential dependence and association amongst markets and can be guided by extreme value theories that offer a perspective on tail dependence. Future research can focus on data defined thresholds and tail dependence, price jumps, long memory process. These approaches can cater for known stylised facts and show how extreme movement in prices can change the relationship amongst the variables during periods of market calmness and turbulences. For instance, it can show how a negative (or positive) change in the price below and above a certain threshold can have differing effects. The studied economies have amongst them some of the most raw commodity-endowed economies that produce global goods that are refined elsewhere globally and imported as altered and finished goods at a cost, strategies such as price targeted trades and Africa based refineries can be immensely beneficial and lessen the level of market price cycle and dependency risk. The potential of an Africa-focused price discrimination strategy for some of the commodities prior to exporting can be used regionally to influence trade especially as current economic advancements are being fuelled by technology and climate sensitive energy demand which is line with potential demand altering of input commodities. The level of dependence amongst the sampled variables also shows that strategies, policies and other ideologies on a micro and macroeconomic level can be conditioned, targeted and based on observable changes in varying sectors of the economy and this effort can be put to use by African governments, asset managers and firms that have exposure in the commodities markets. The high level of dependence observed in the currencies can bolster and improve trade amongst economies.

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Appendix A. Normal Distribution Assumption

The charts presented in the current section show histograms and normality quantile-to-quantile (q-q) plots of the univariate return series per economy. Each figure represents an initial visual assessment of the marginal returns' structure showing cases where there is significant skewness and violation of normality and are used in conjunction with JB and SW normality tests in Table 4.3 to assess reasonability of assuming that the data is normally distributed. Each figure shows a comparison of a theoretical estimated normally distributed model that has similar characteristics (in terms of mean and variation) with the distribution of the univariates. In each figure, an estimated normal distribution is shown by the solid grey and blue lines in the histogram QQ plots, respectively. Based on the histogram central concentration and QQ plots' tail behaviour, skewness (asymmetry), excess kurtosis (leptokurtic), SW and JB tests; none of the sampled variables can be regarded as being normally distributed, proving common stylised facts about the behaviour of financial data.

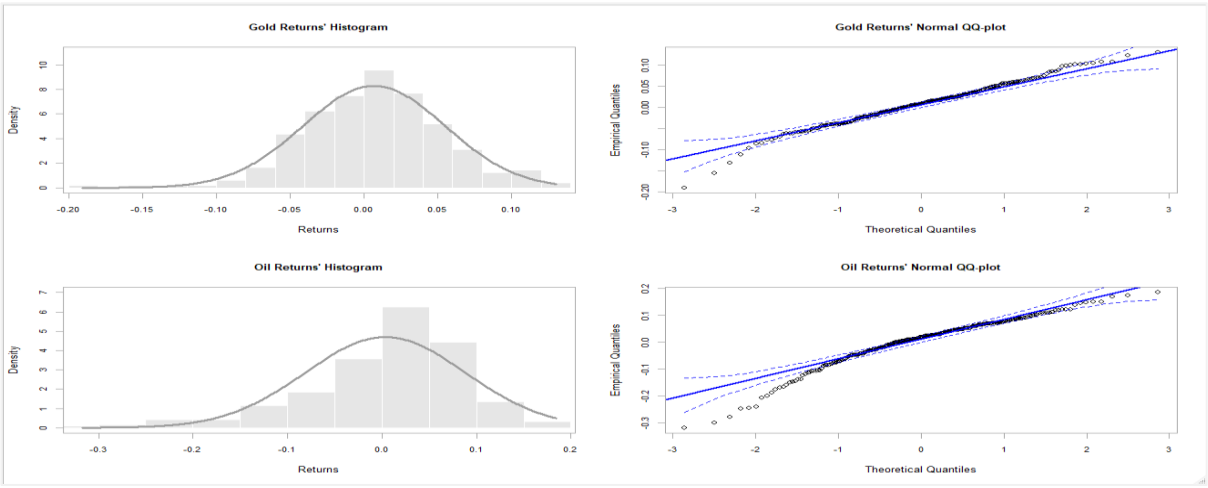

Figure A.1: Commodities' Returns' Histogram and Q-Q Plots

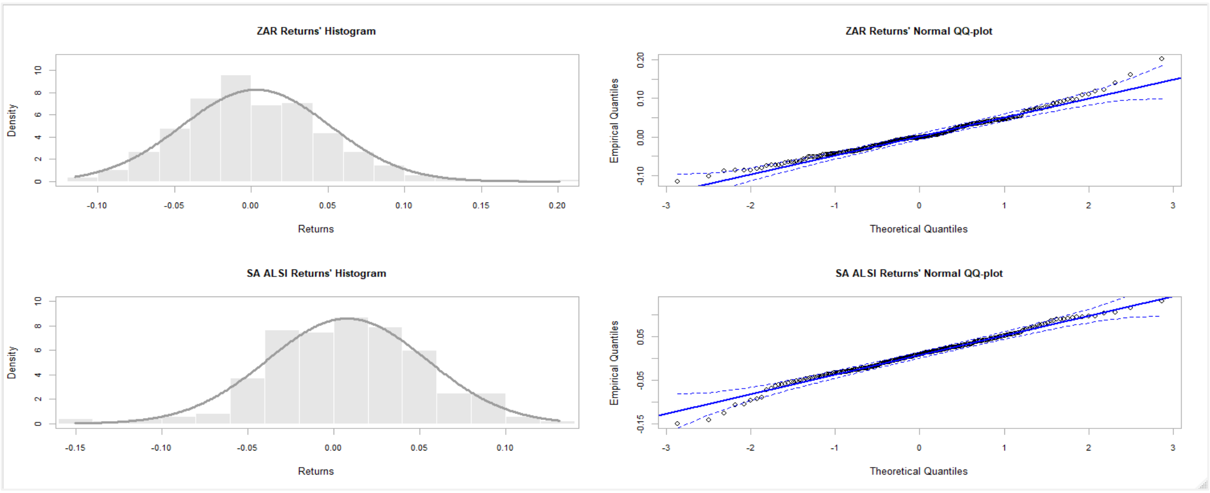

Figure A.2: South Africa Variables' Returns' Histogram and Q-Q Plots

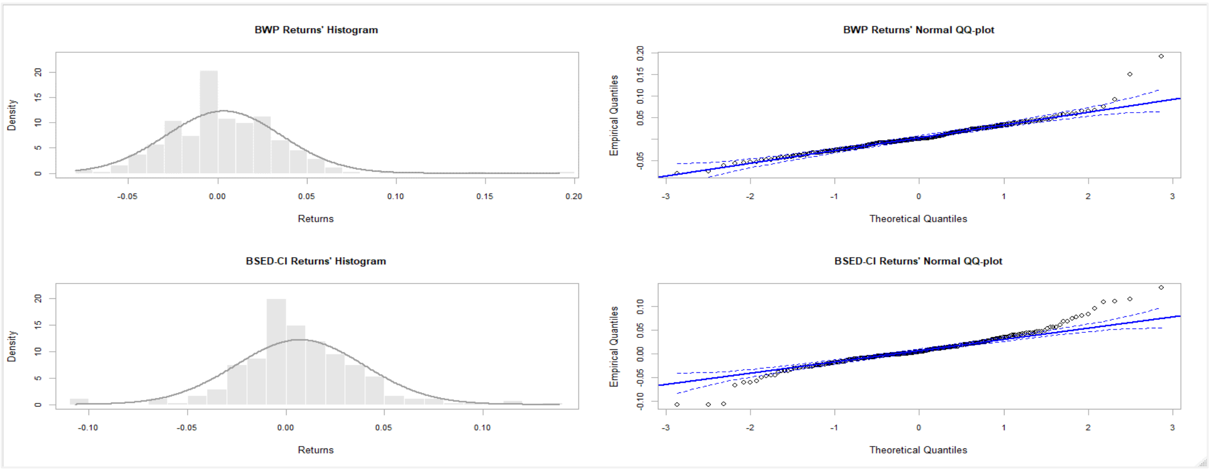

Figure A.3: Botswana Variables' Returns' Histogram and Q-Q Plots

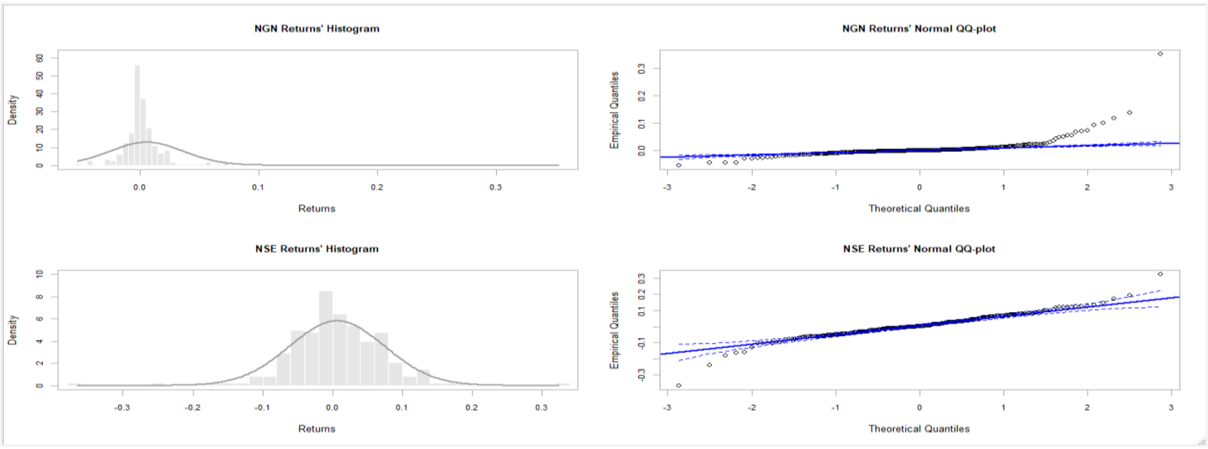

Figure A.4: Nigeria Variables' Returns' Histogram and Q-Q Plots

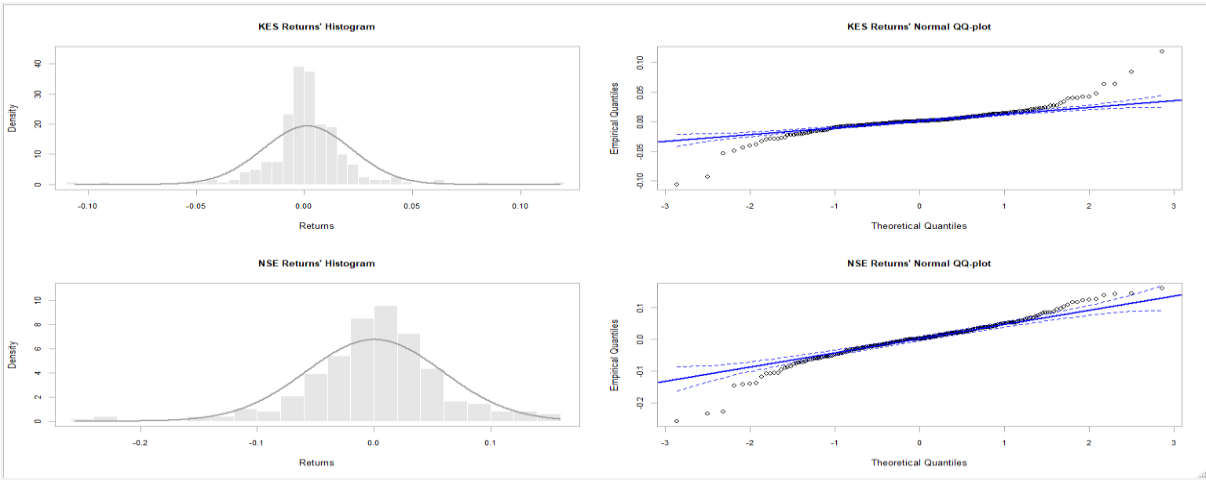

Figure A.5: Kenya Variables' Returns' Histogram and Q-Q Plots

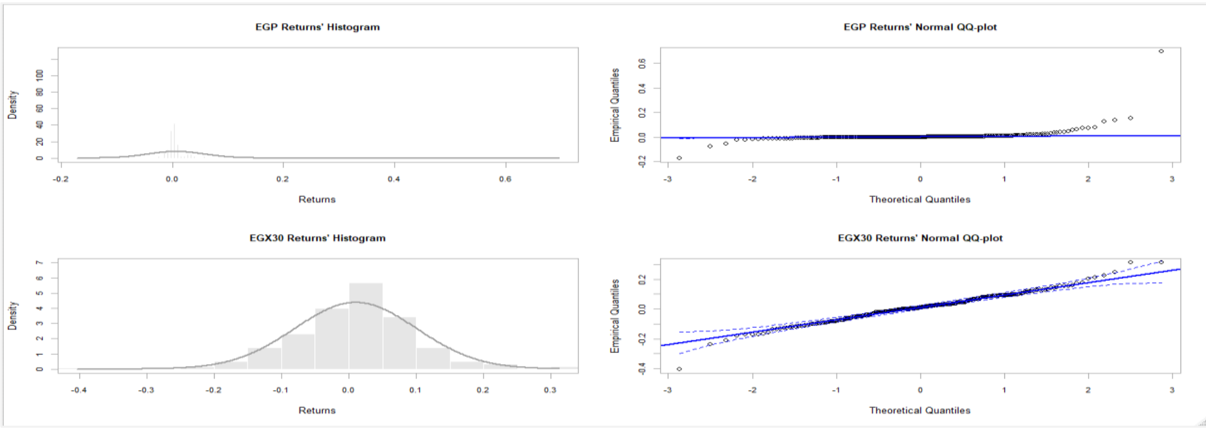

Figure A.6: Arab Republic of Egypt Variables' Returns' Histogram and Q-Q Plots

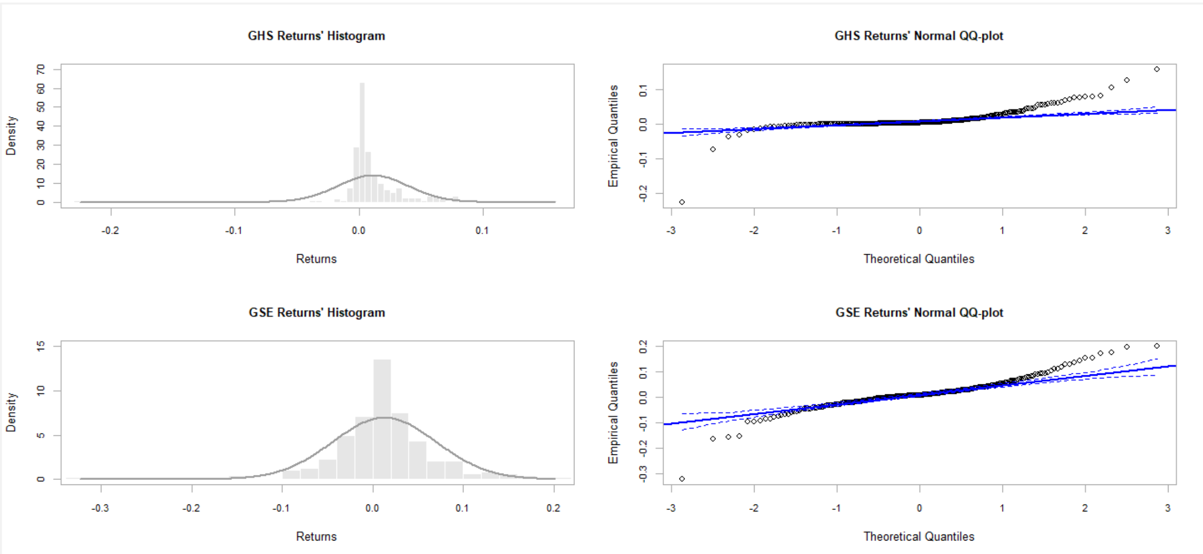

Figure A.7: Ghana Variables' Returns' Histogram and Q-Q Plots

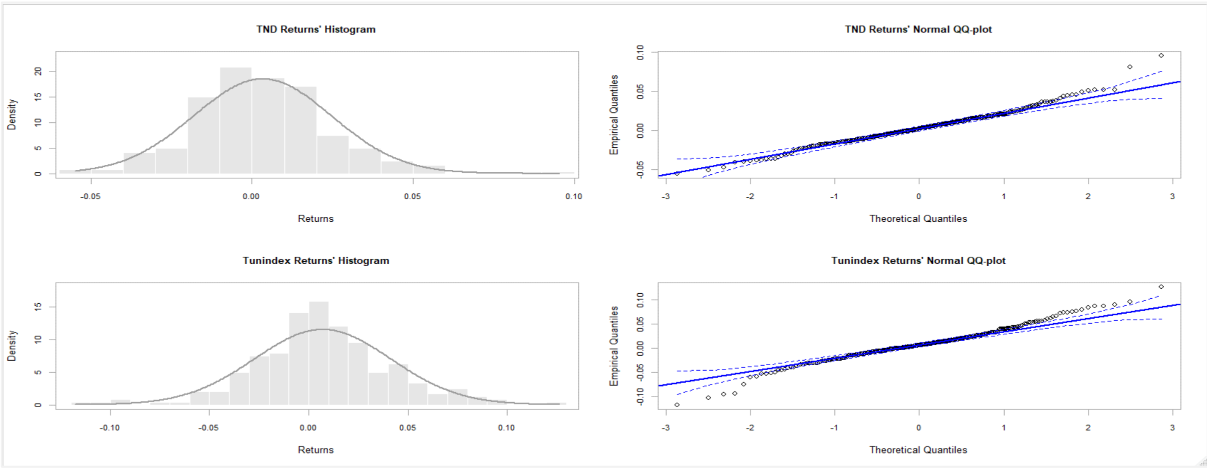

Figure A.8: Tunisia Variables' Returns' Histogram and Q-Q Plots

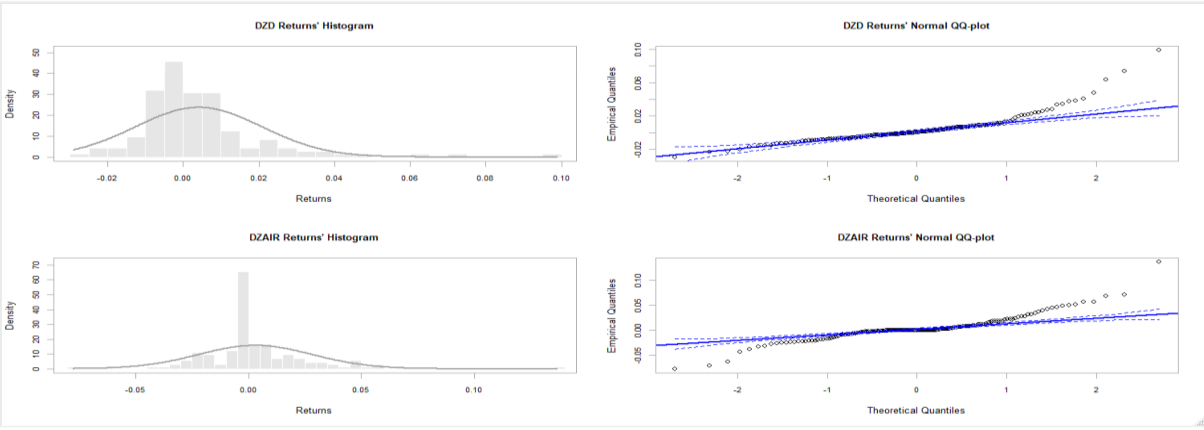

Figure A.9: Algeria Variables' Returns' Histogram and Q-Q Plots

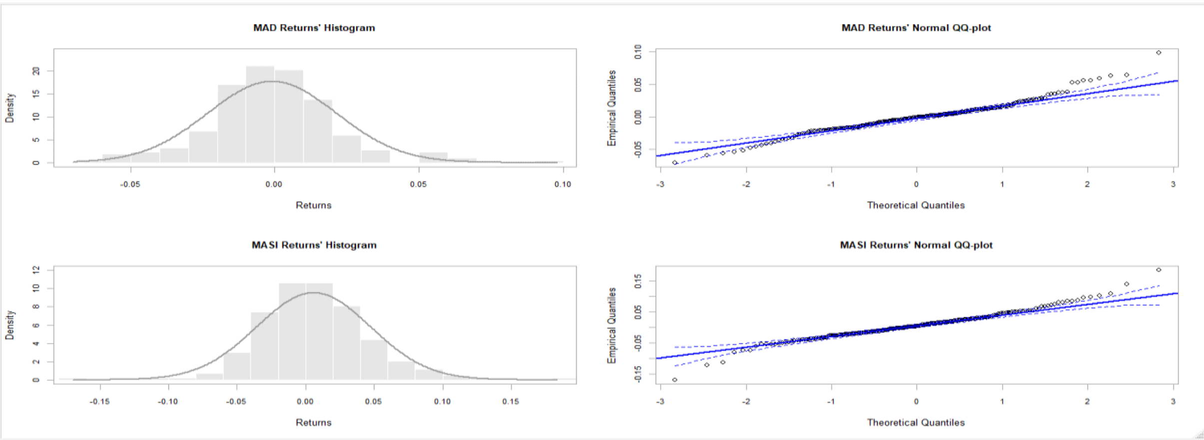

Figure A.10: Morocco Variables' Returns' Histogram and Q-Q Plots

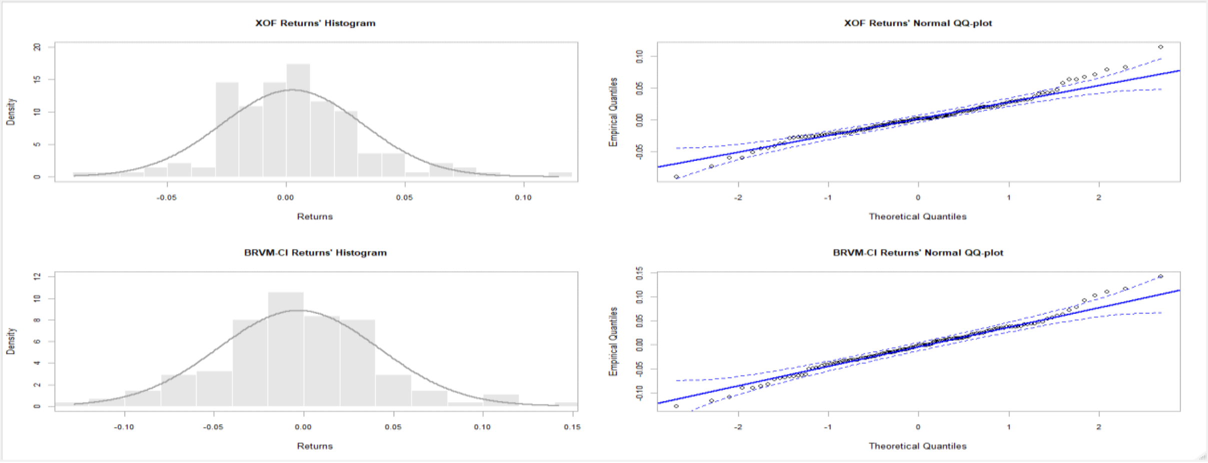

Figure A.11: Côte d'Ivoire Variables' Returns' Histogram and Q-Q Plots

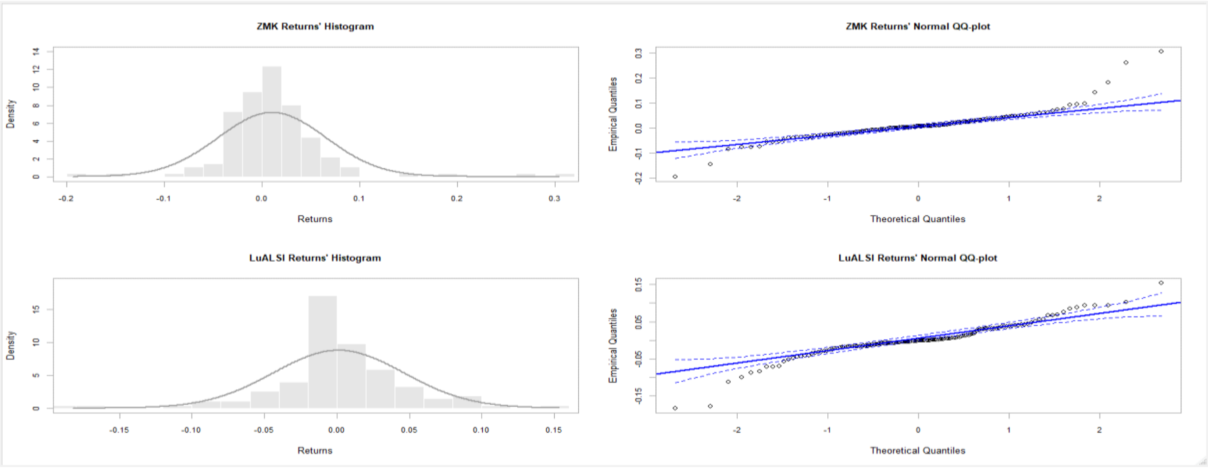

Figure A.12: Zambia Variables' Returns' Histogram and Q-Q Plots

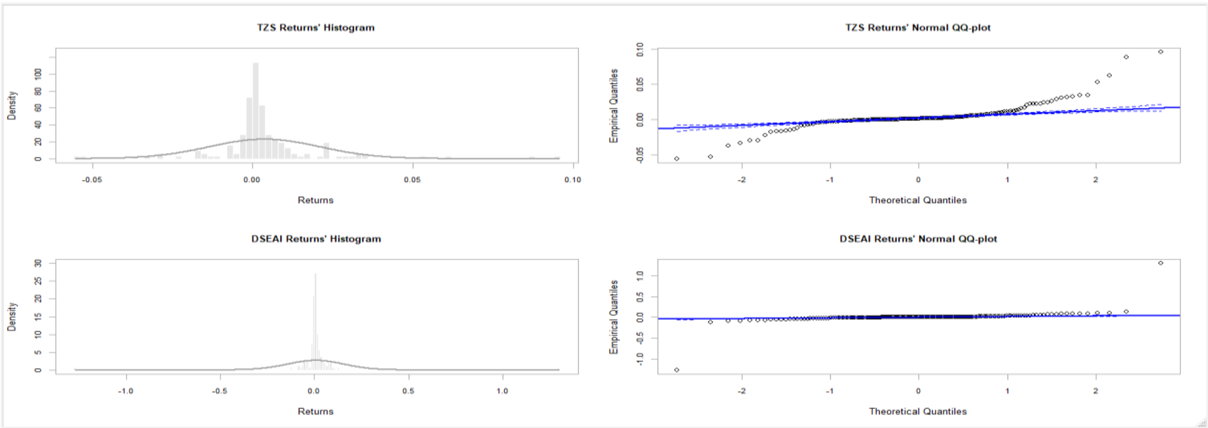

Figure A.13: Tanzania Variables' Returns' Histogram and Q-Q Plots

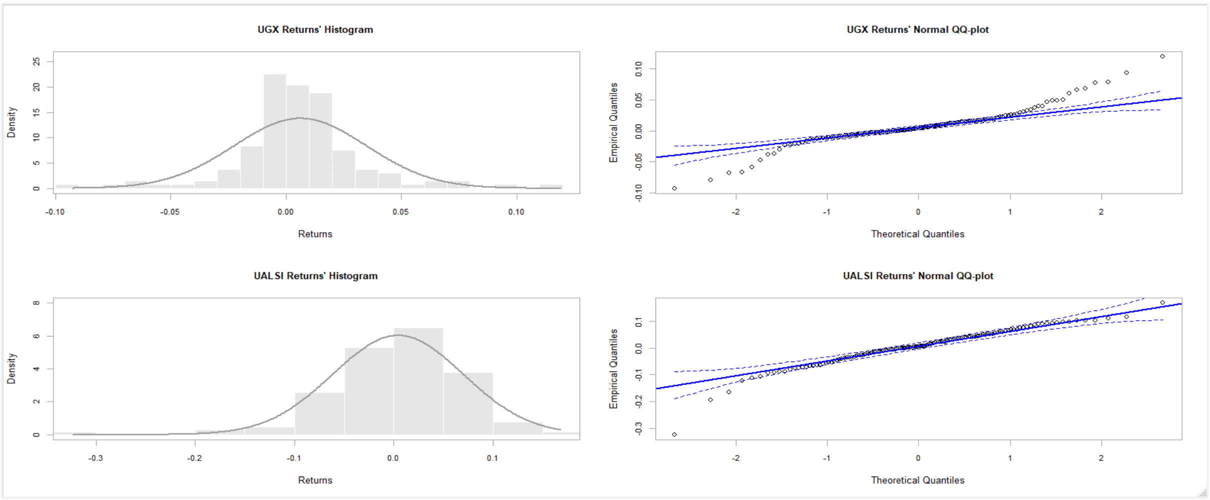

Figure A.14: Uganda Variables' Returns' Histogram and Q-Q Plots

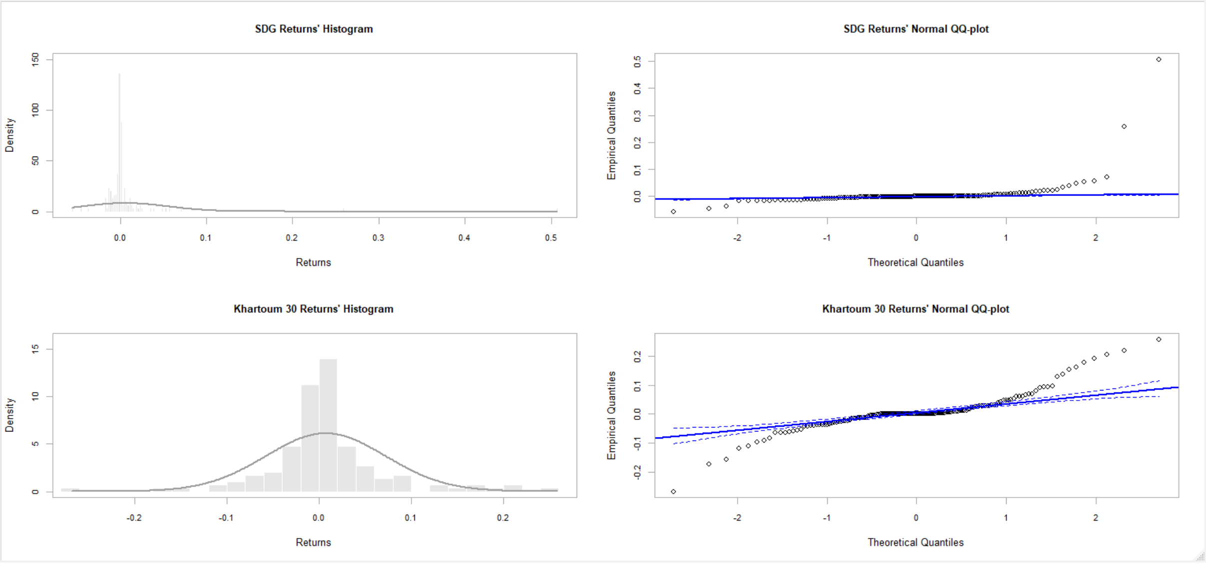

Figure A.15: Sudan Variables' Returns' Histogram and Q-Q Plots

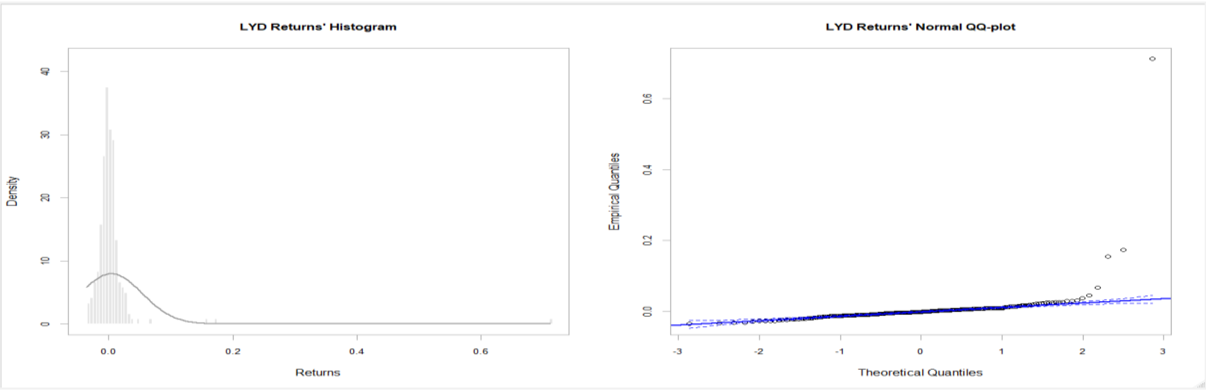

Figure A.16: Libya Variables' Returns' Histogram and Q-Q Plots

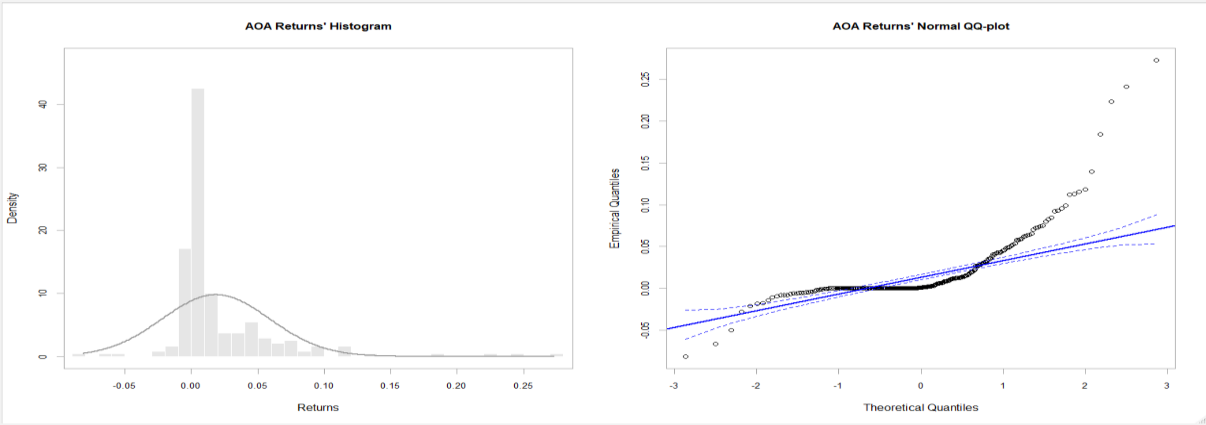

Figure A.17: Angola Variables' Returns' Histogram and Q-Q Plots

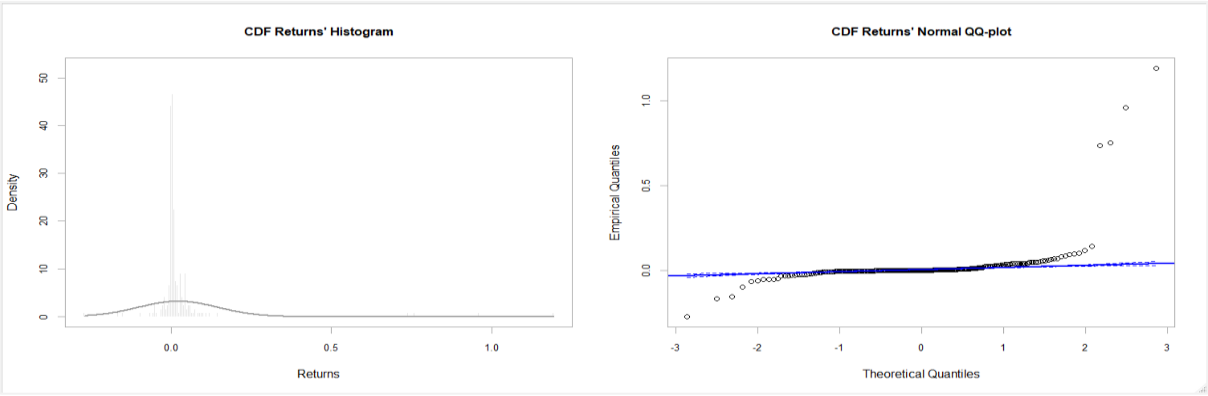

Figure A.18: DR. Congo Variables' Returns' Histogram and Q-Q Plots

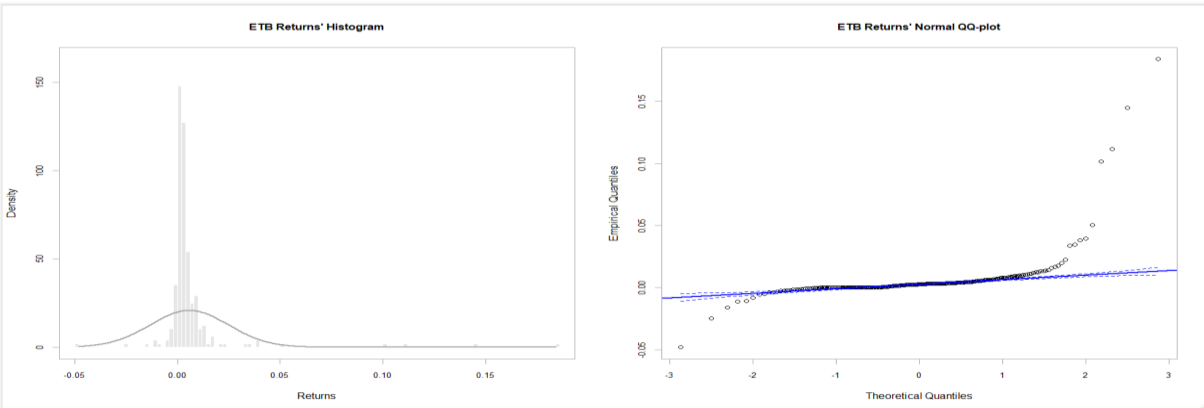

Figure A.19: Ethiopia Variables' Returns' Histogram and Q-Q Plots

Appendix B. Correlograms

This subsection shows the autocorrelation or lag (k) correlation coefficients, which is the relationship that exists between the return at time t, r_t, and its past forms $\{r_{t-1}, r_{t-2}, \dots r_{t-k}\}$. The lag (k) correlation shows the impact or the dependence of the current return value on its past returns and will be used to show if there is a need to asses past returns and to determine their influence on current value of the returns so their influence is included and modelled. The presence of serial dependence is shown in the figures below using sample autocorrelation (ACF) and partial autocorrelation (PACF) functions of each sampled variable's residuals.

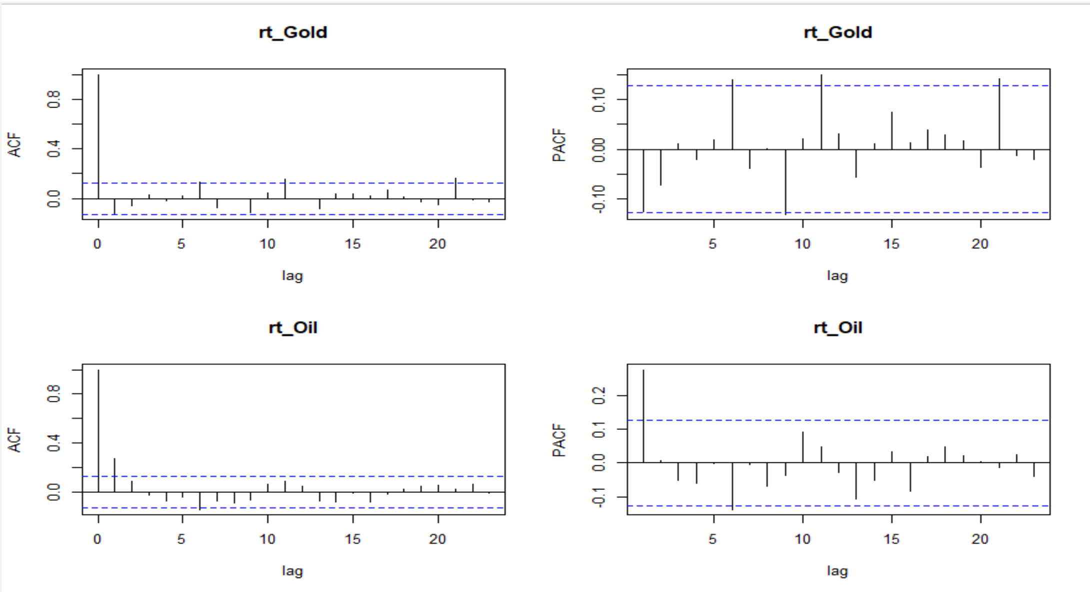

Figure B.1: ACF and PACF of Gold and Crude Oil

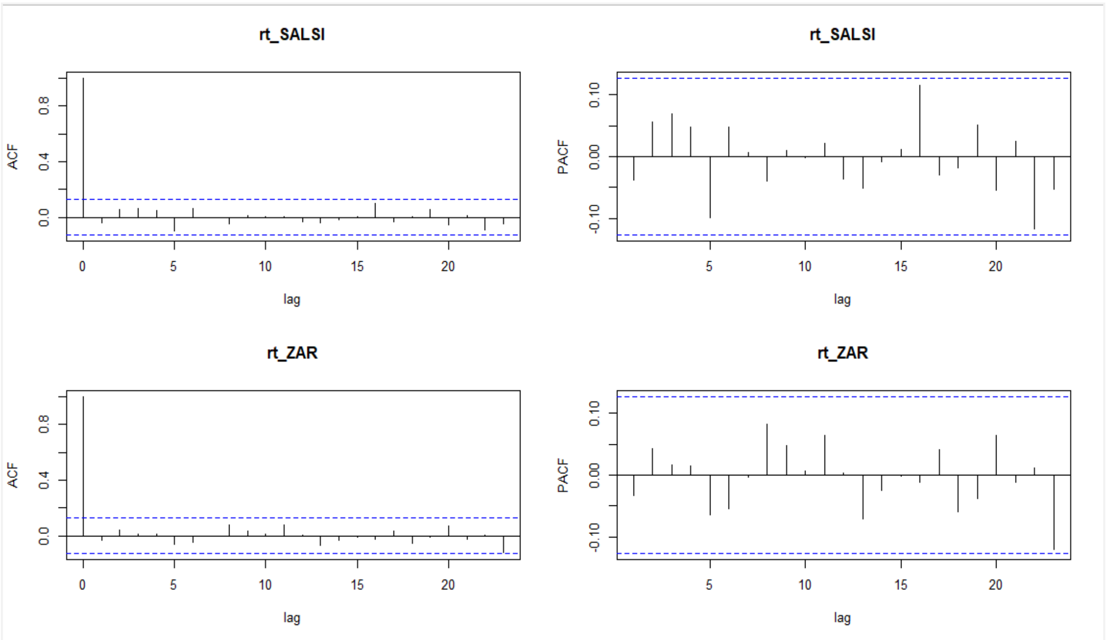

Figure B.2: ACF and PACF of South Africa's ALSI and ZAR

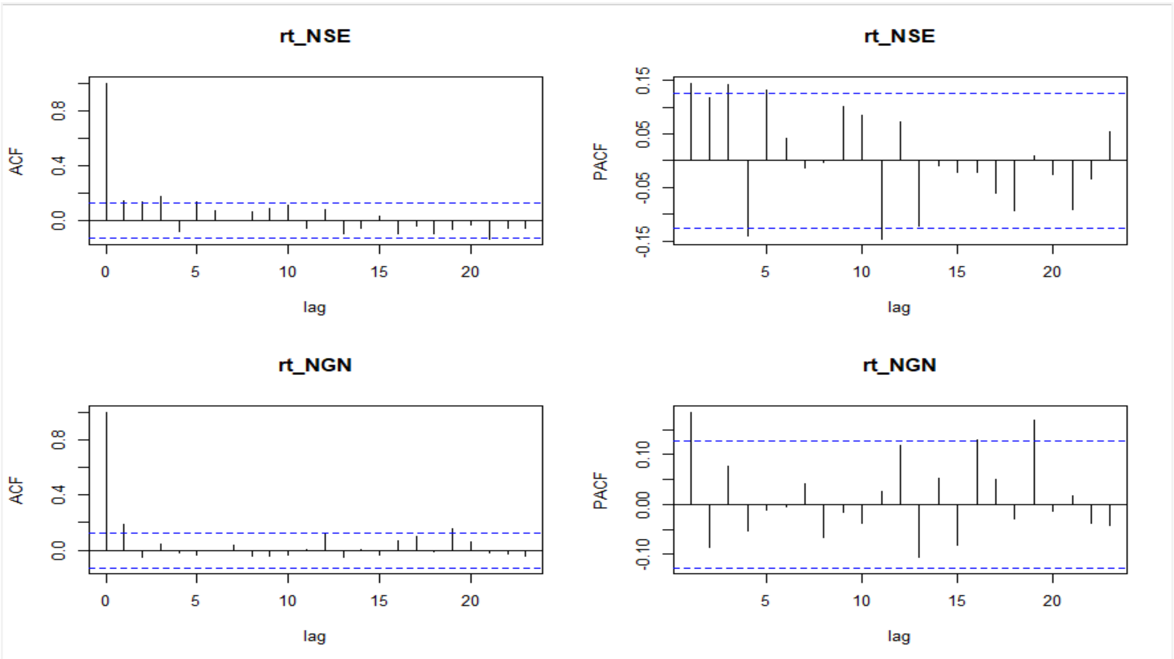

Figure B.3: ACF and PACF Nigeria's NSE and NGN

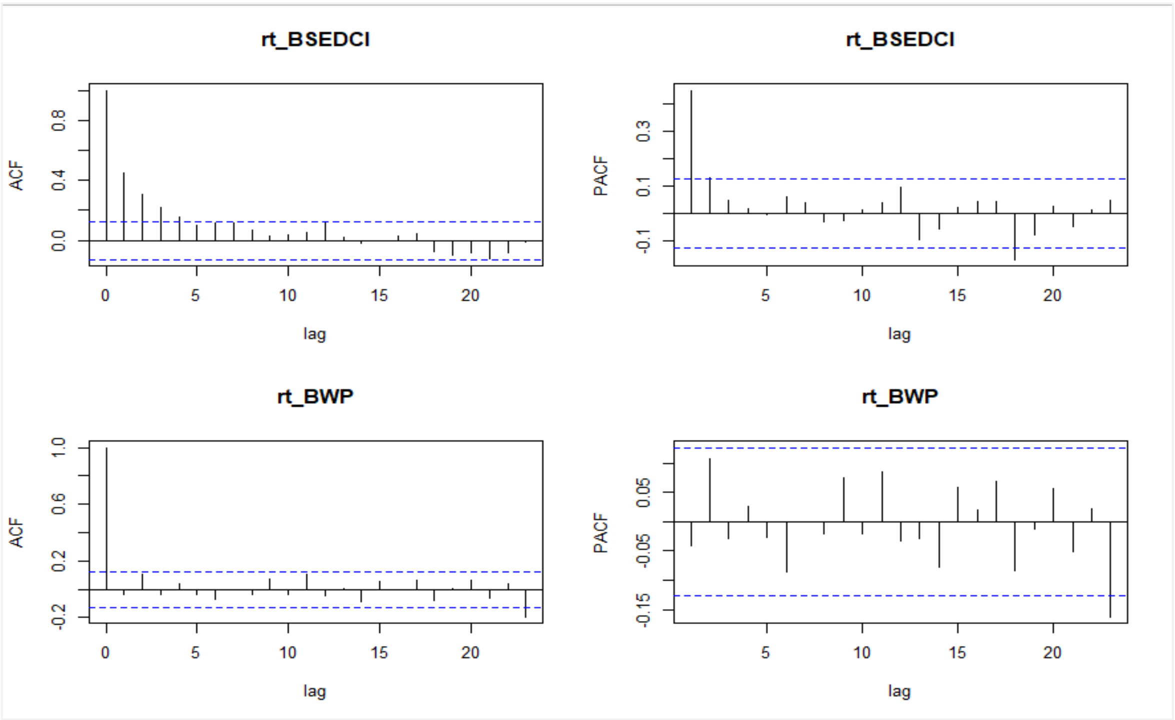

Figure B.4: ACF and PACF Botswana's BSEDCI and BWP

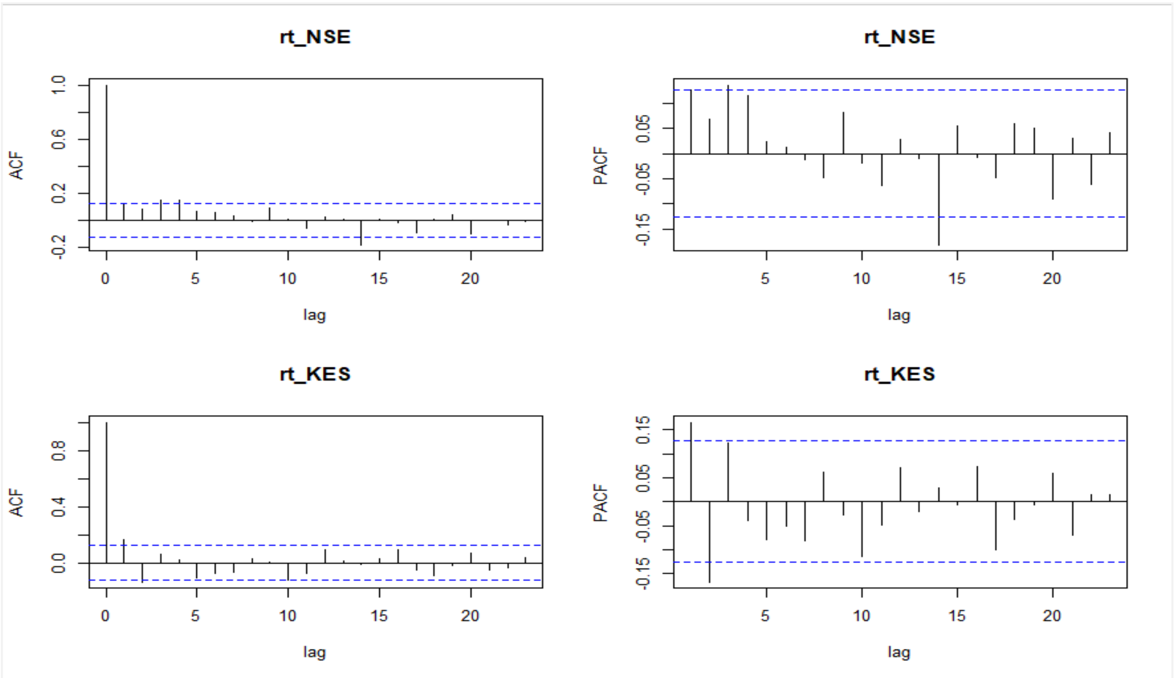

Figure B.5: ACF and PACF Kenya's NSE and KES

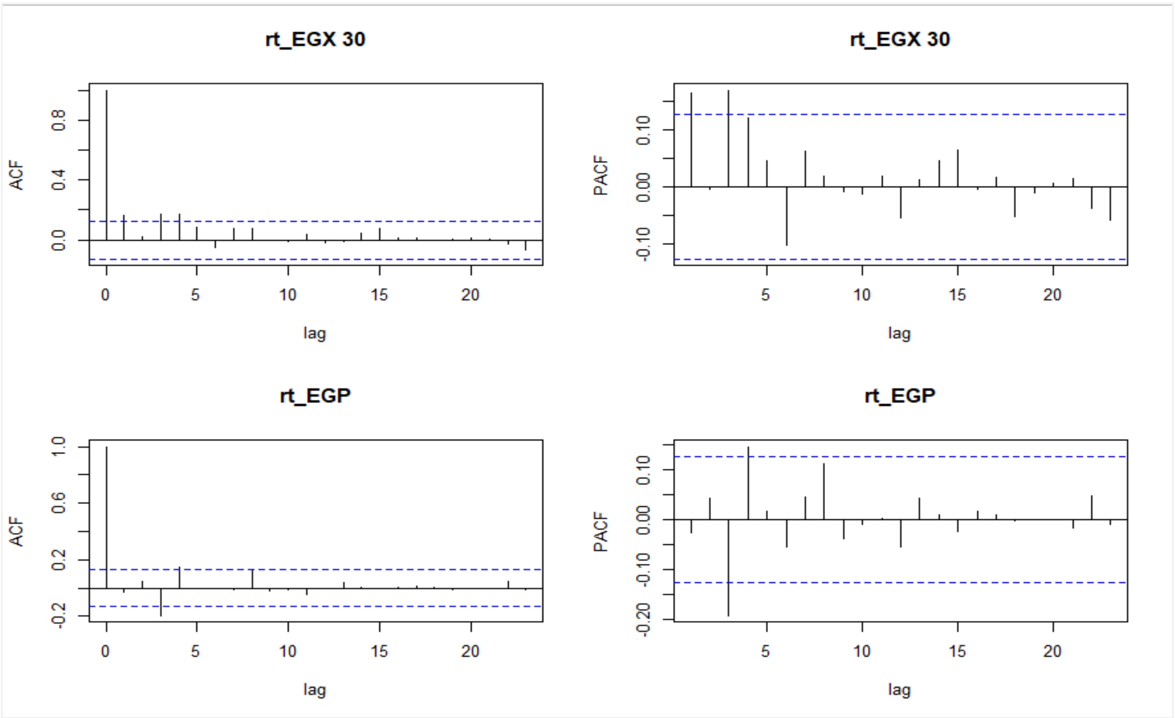

Figure B.6: ACF and PACF Arab Republic of Egypt's EGX 30 and EGP

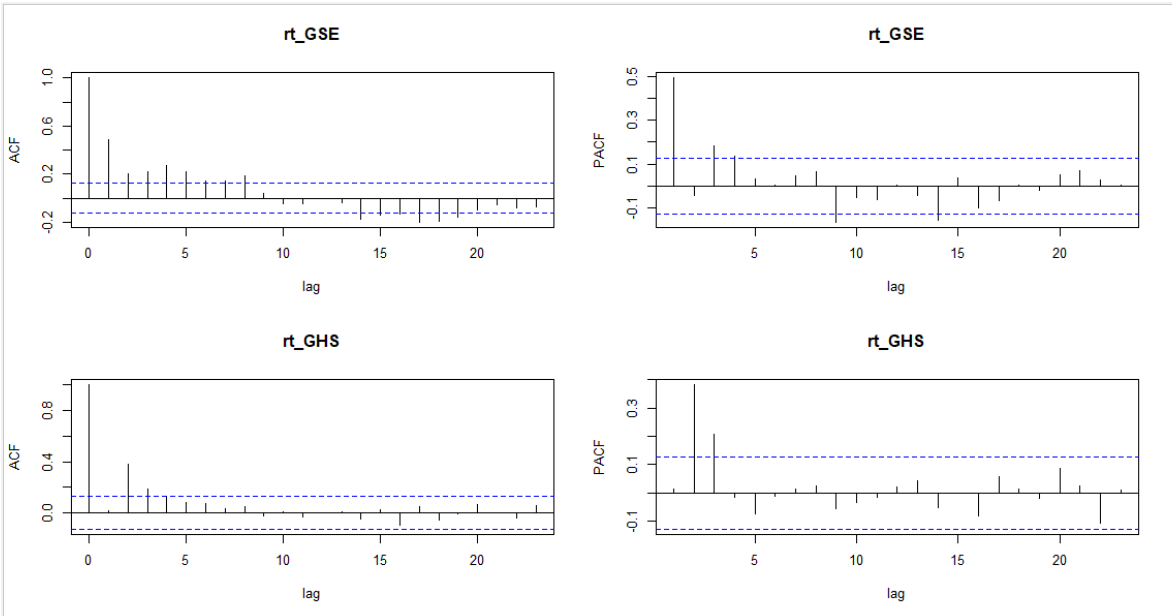

Figure B.7: ACF and PACF Ghana's GSE and GHS

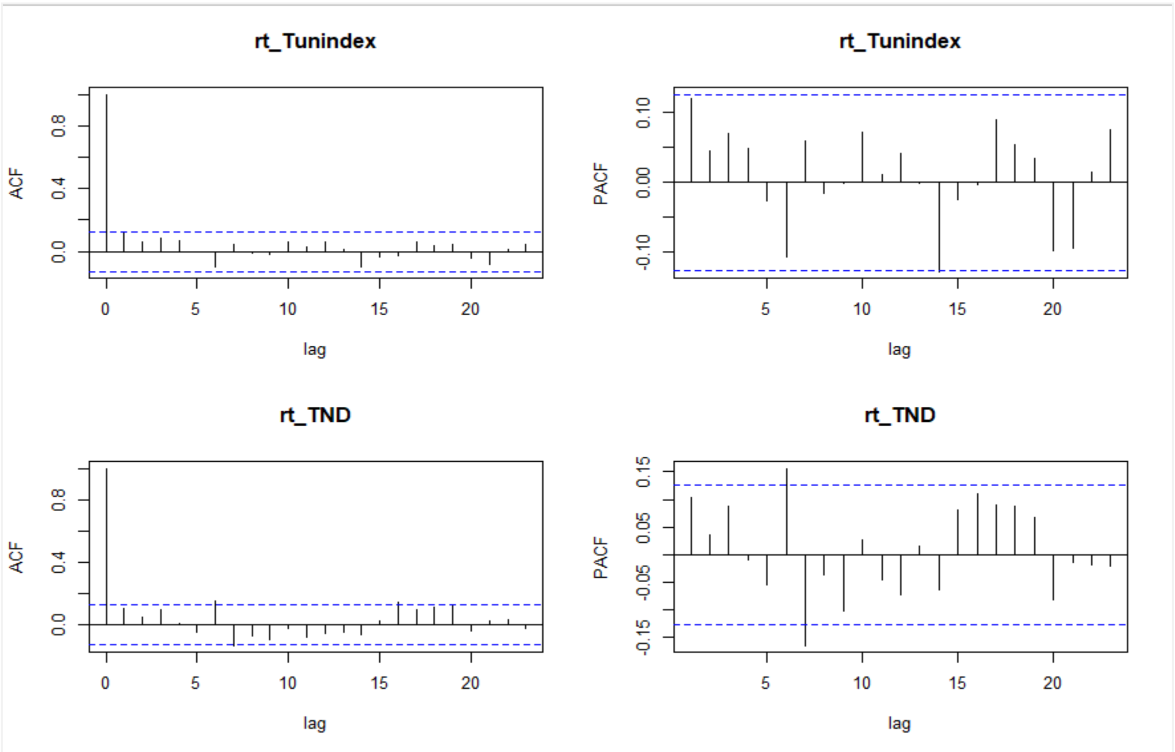

Figure B.8: ACF and PACF Tunisia's Tunindex and TND

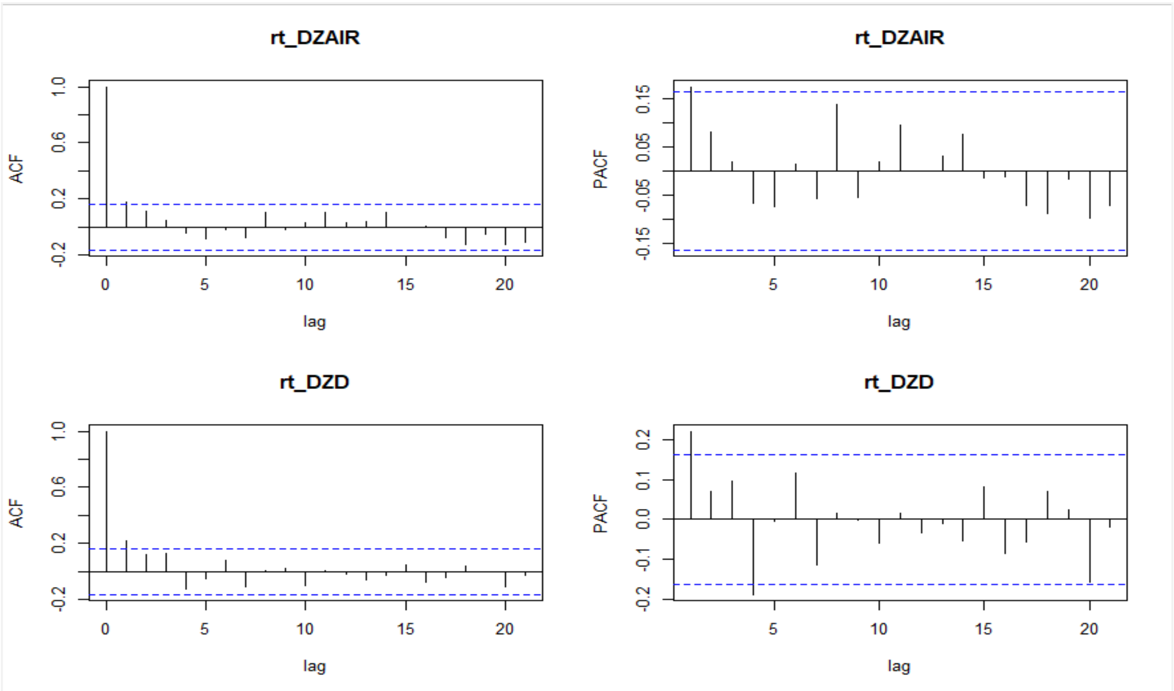

Figure B.9: ACF and PACF Algeria DZAIR and DZD

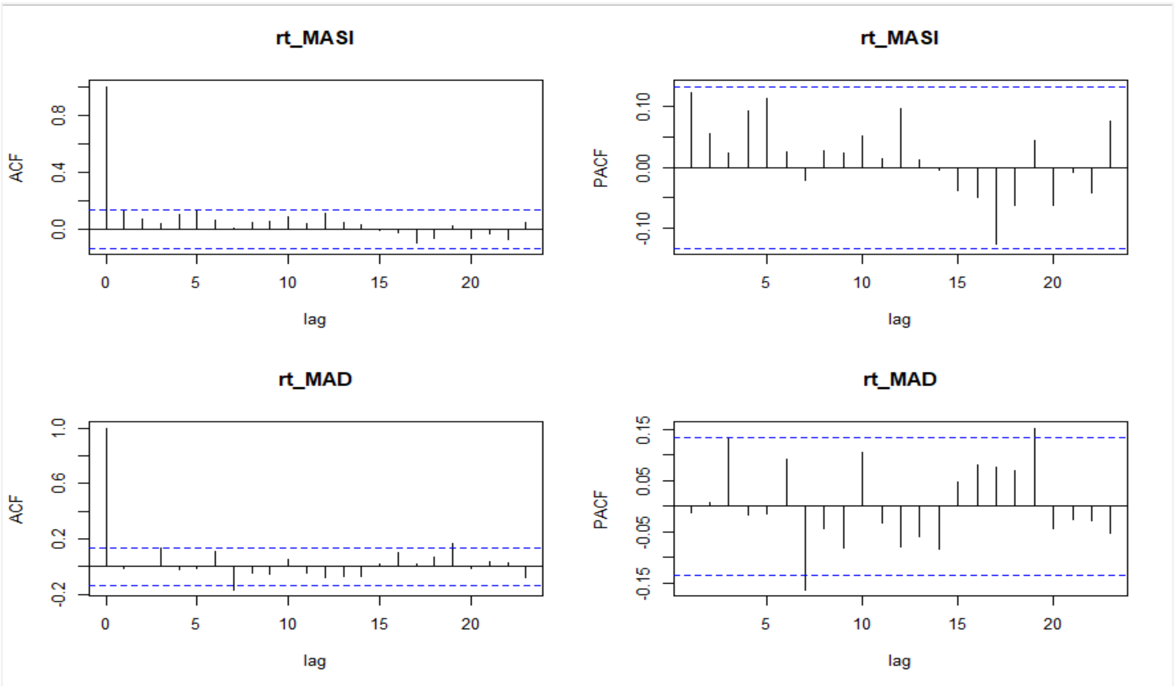

Figure B.10: ACF and PACF Morocco MASI and MAD

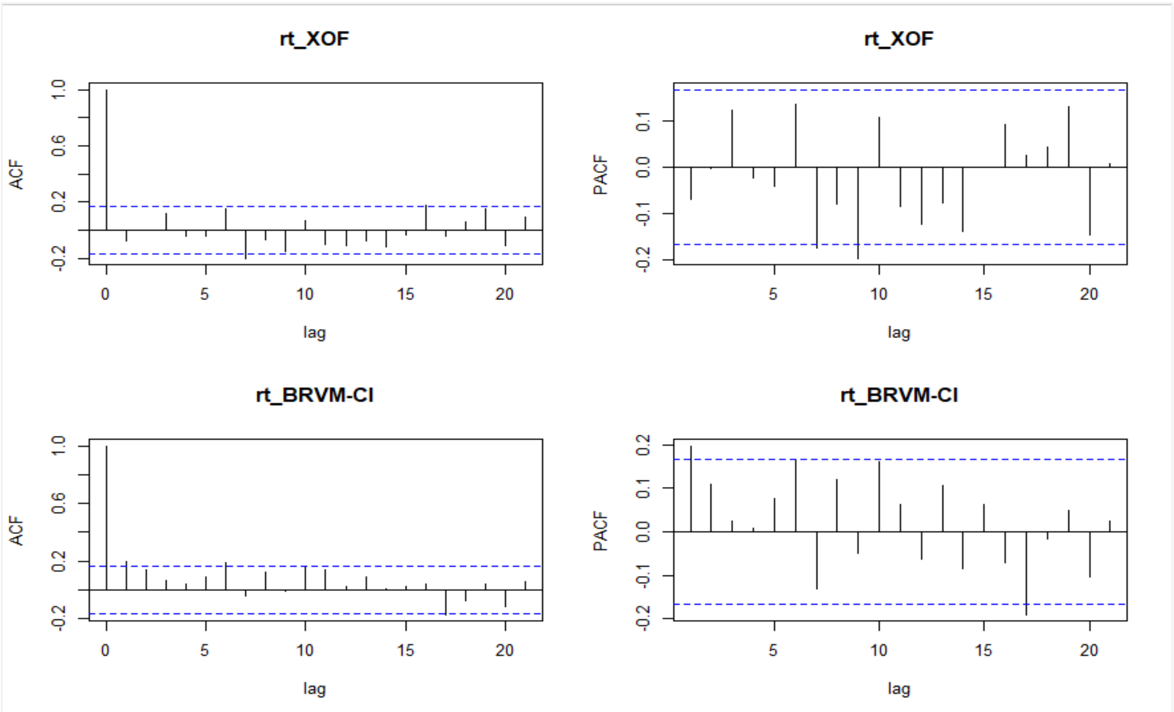

Figure B.11: ACF and PACF Côte d'Ivoire XOF and BRVMCI

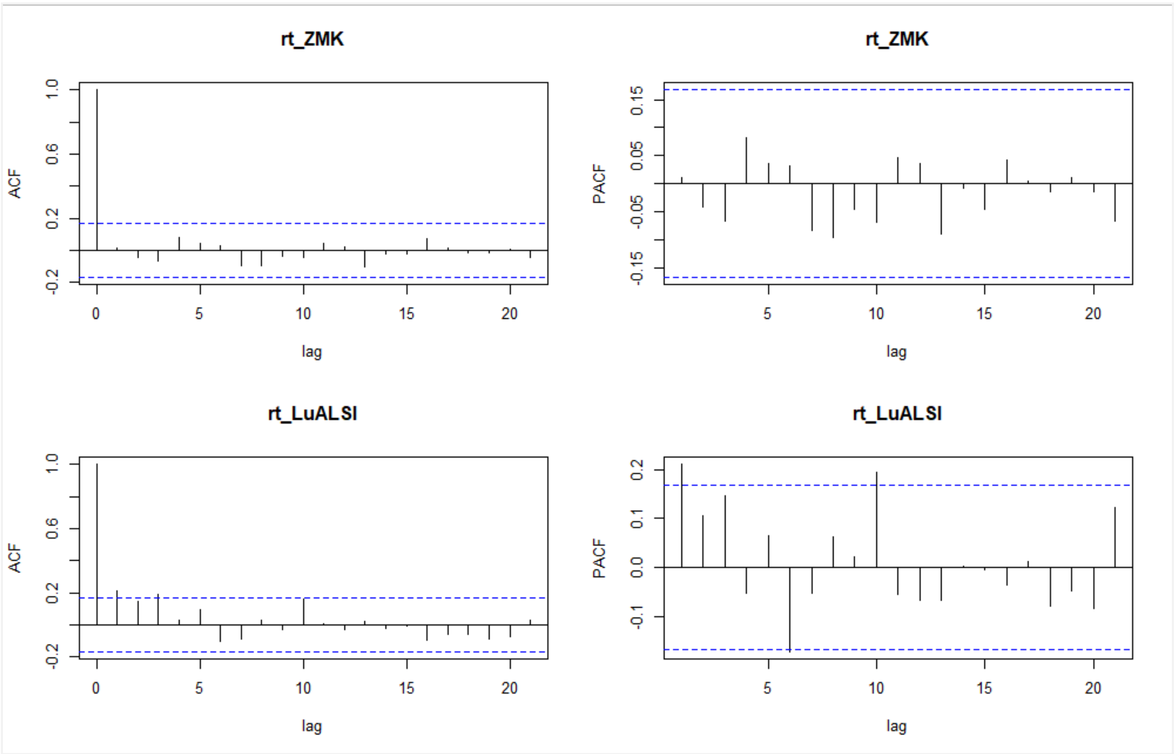

Figure B.12: ACF and PACF Zambia’s ZMK and LuALSI

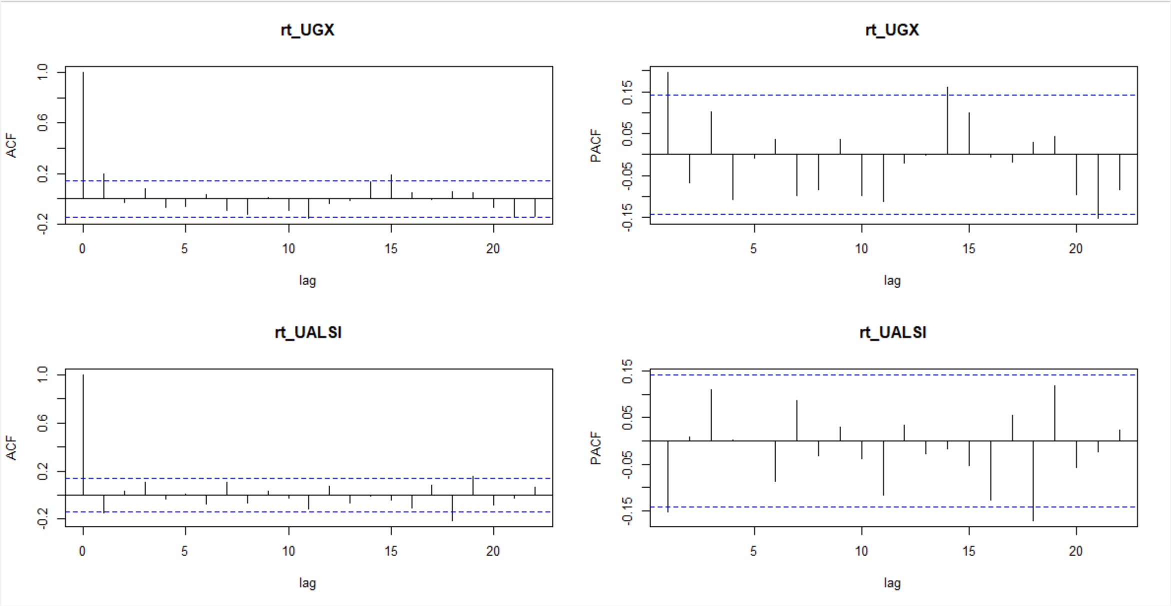

Figure B.13: ACF and PACF Uganda’s UGX and UALSI

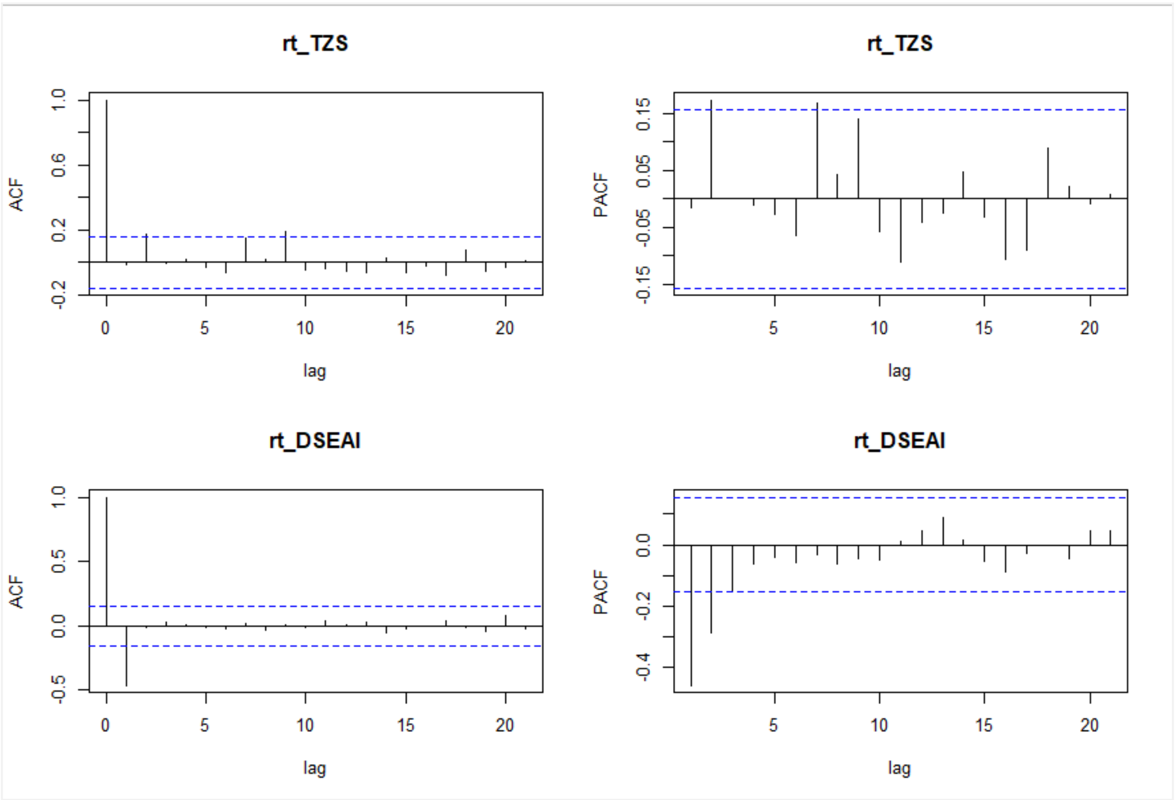

Figure B.14: ACF and PACF Tanzania's TZS and DSEAI

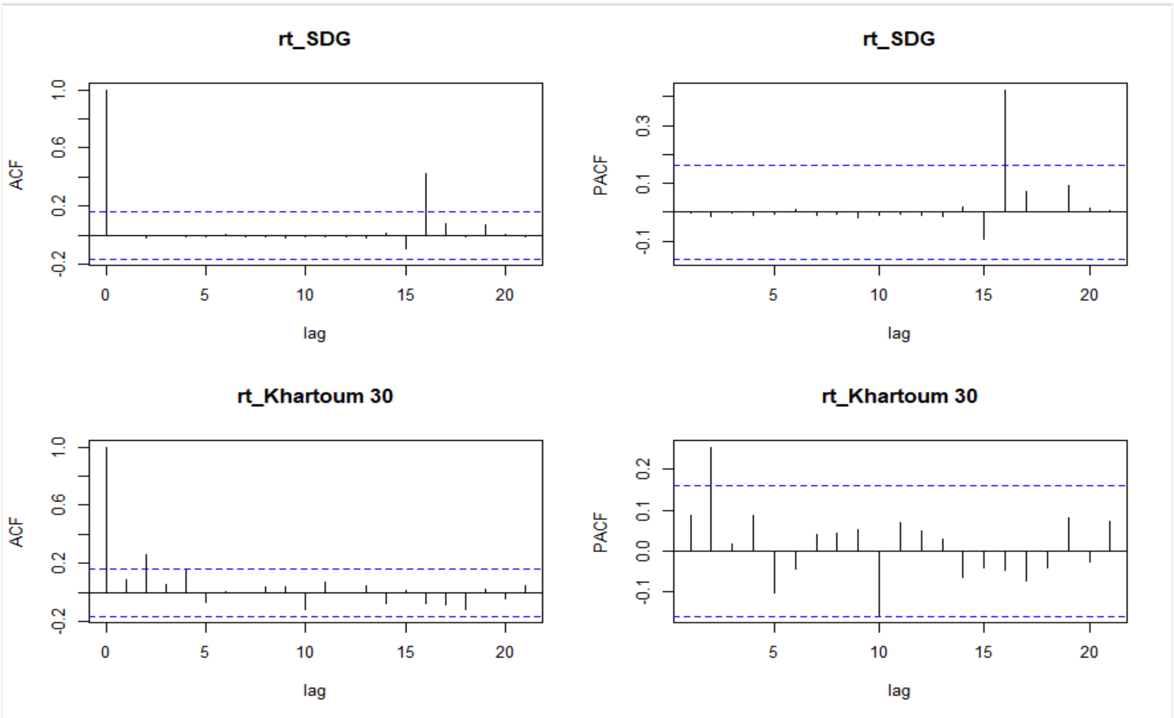

Figure B.15: ACF and PACF Sudan SDG and Khartoum 30

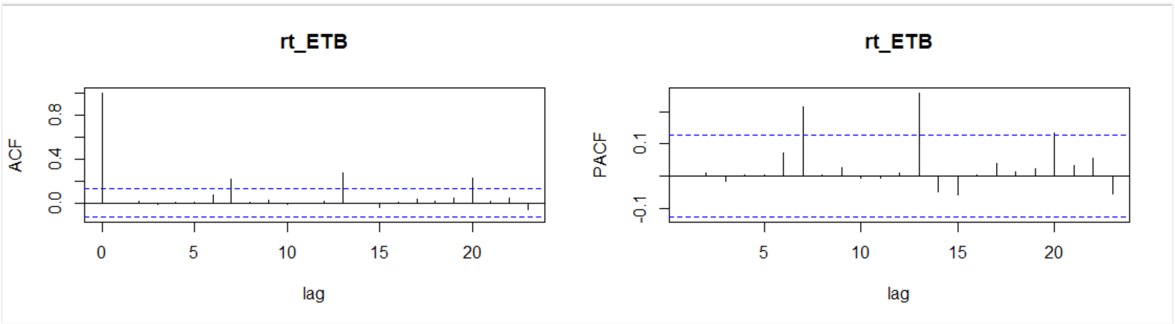

Figure B.16: ACF and PACF Ethiopia’s ETB

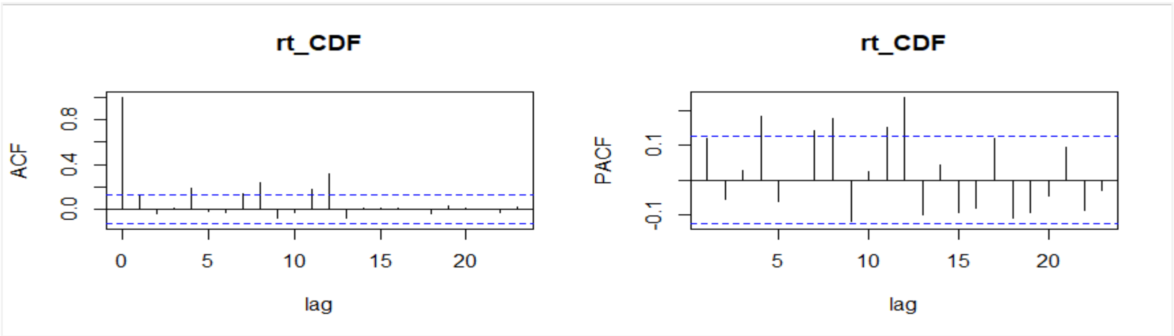

Figure B.17: ACF and PACF DR. Congo’s CDF

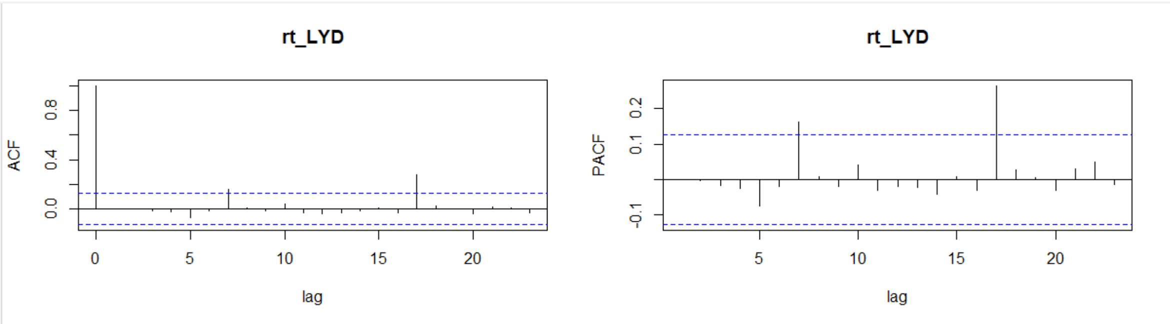

Figure B.18: ACF and PACF Libya’s LYD

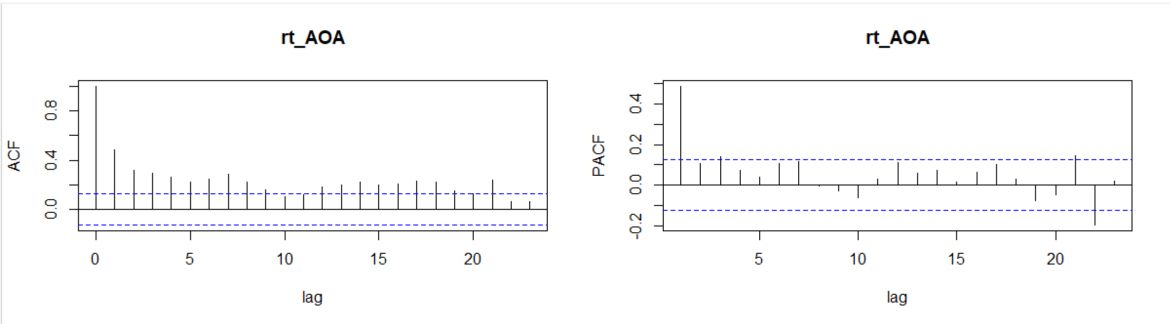

Figure B.19: ACF and PACF Angola’s AOA

Appendix C. Dependograms

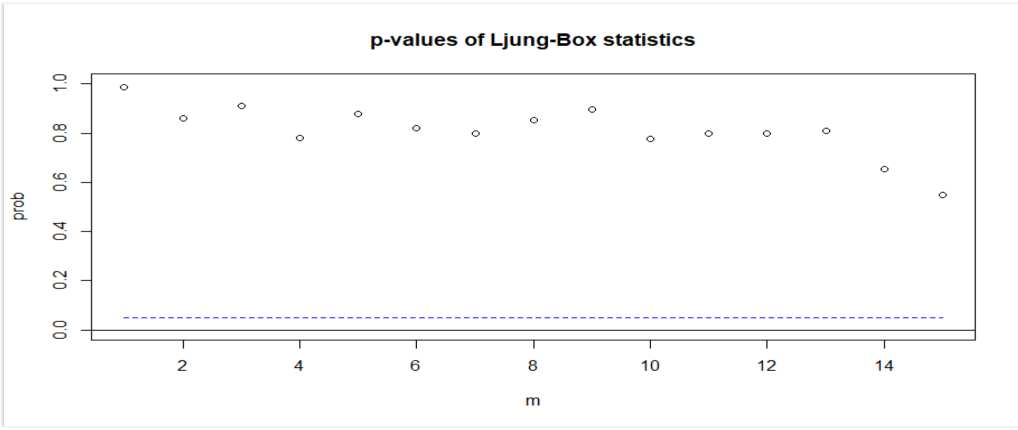

Figure C.1: Angola Ljung–Box Dependogram

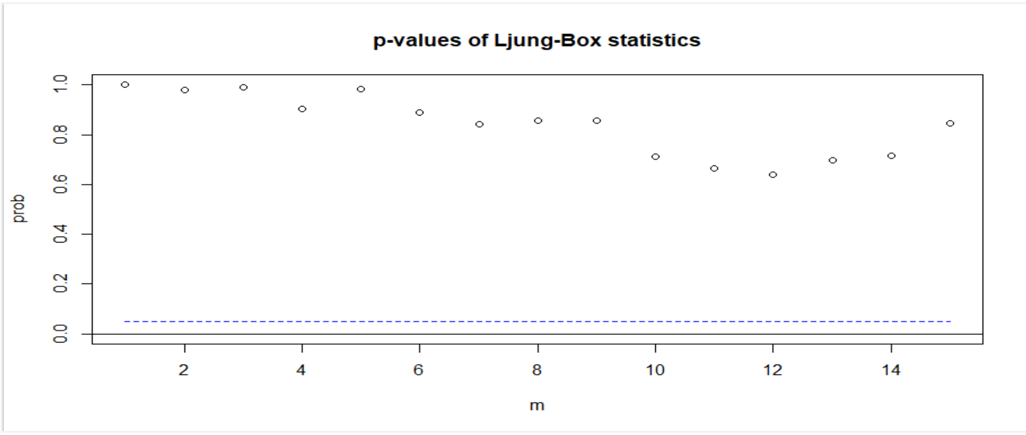

Figure C.2: Botswana Ljung–Box Dependogram

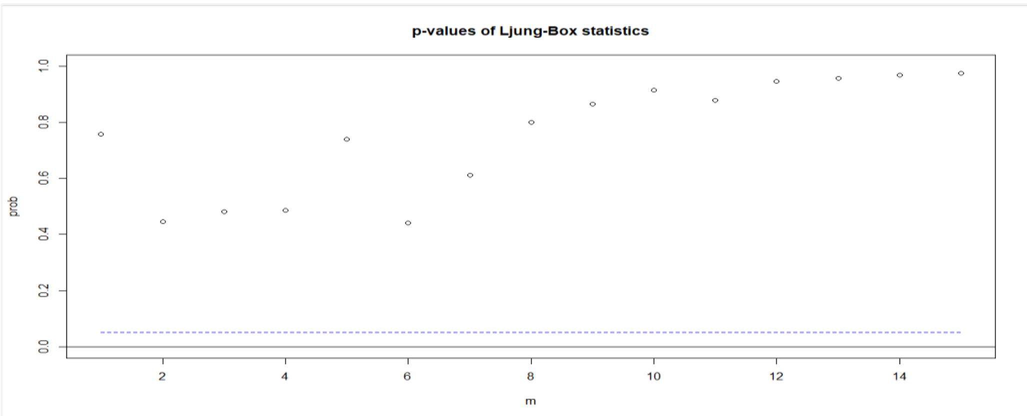

Figure C.3: DRC Ljung–Box Dependogram

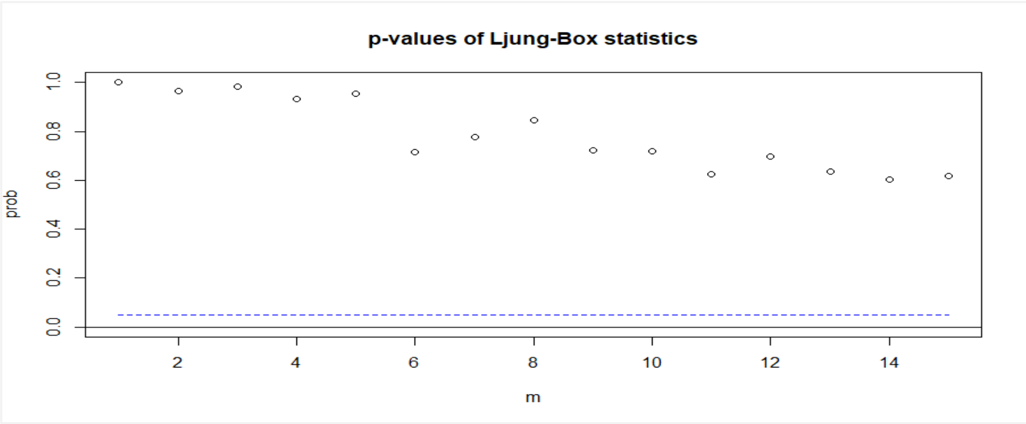

Figure C.4: Côte d’Ivoire Ljung–Box Dependogram

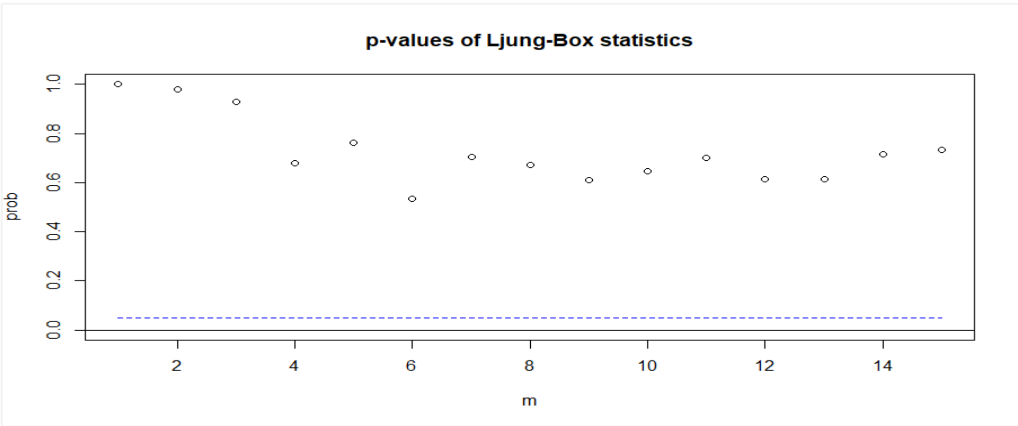

Figure C.5: Egypt Ljung–Box Dependogram

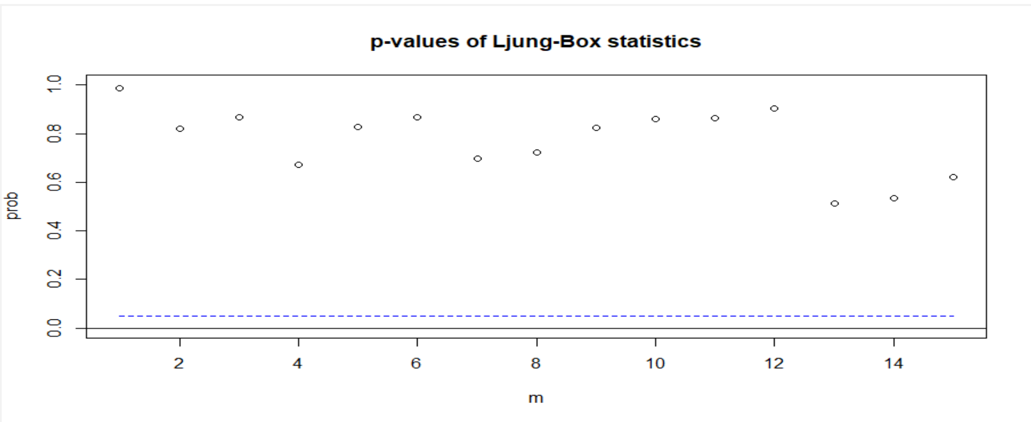

Figure C.6: Ethiopia Ljung–Box Dependogram

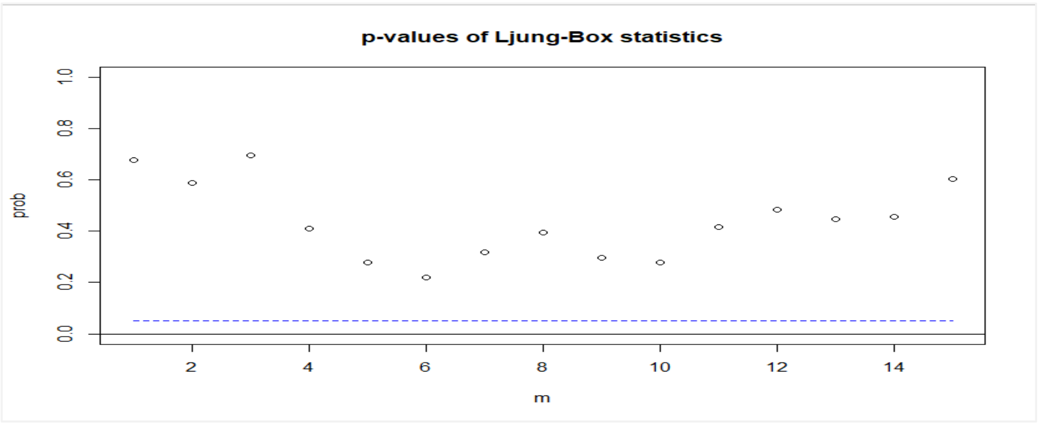

Figure C.7: Ghana Ljung–Box Dependogram

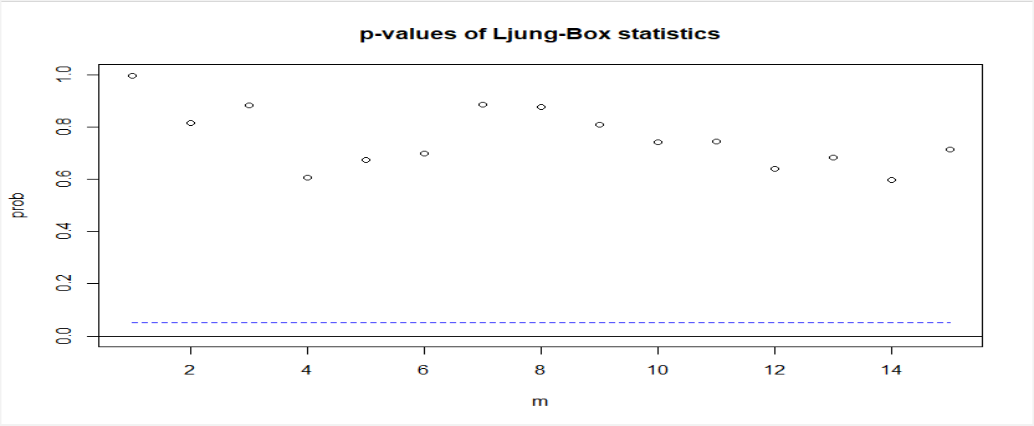

Figure C.8: Kenya Ljung–Box Dependogram

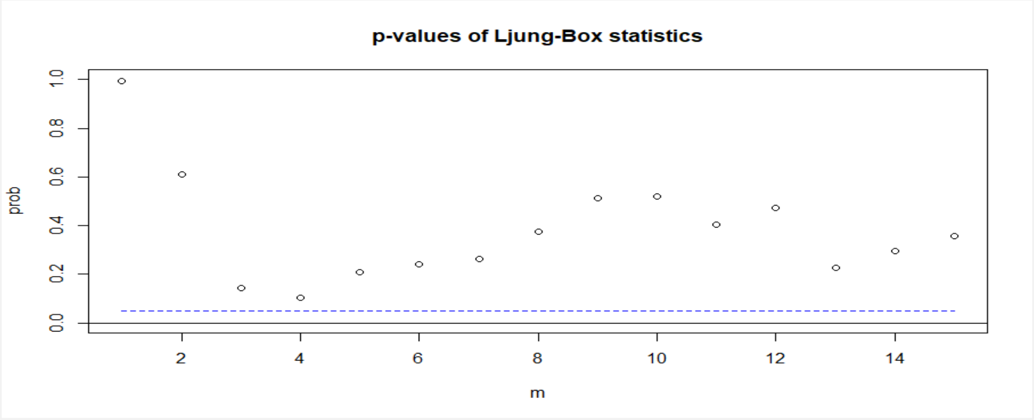

Figure C.9: Libya Ljung–Box Dependogram

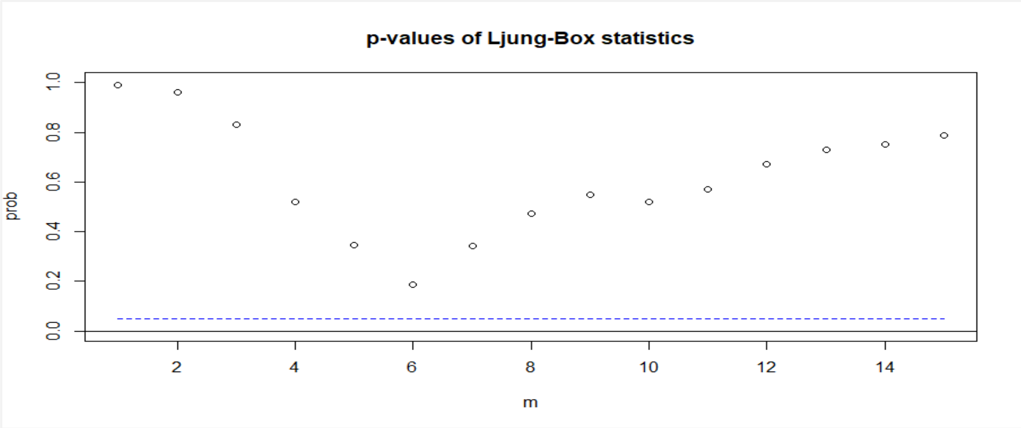

Figure C.10: Morocco Ljung–Box Dependogram

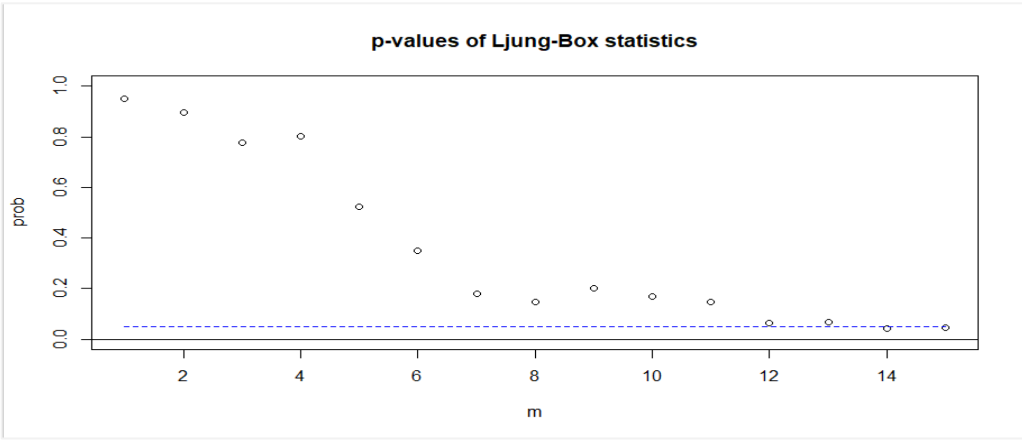

Figure C.11: Nigeria Ljung–Box Dependogram

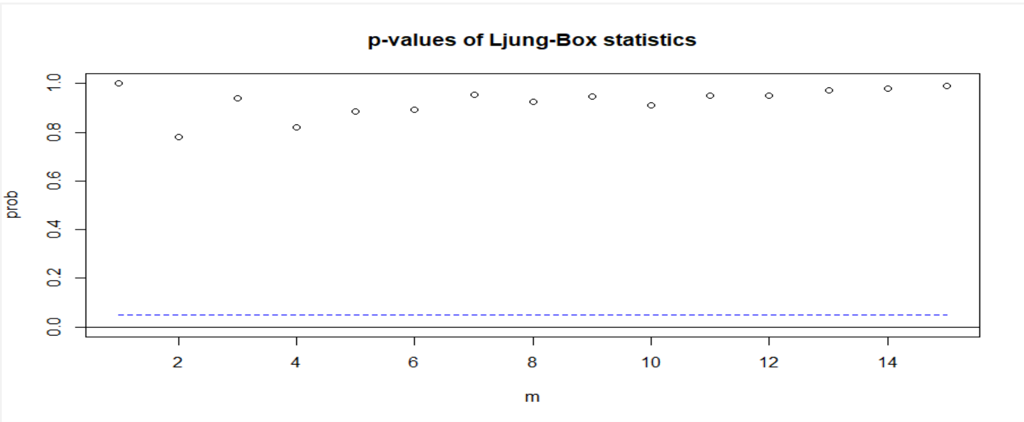

Figure C.12: South Africa Ljung–Box Dependogram

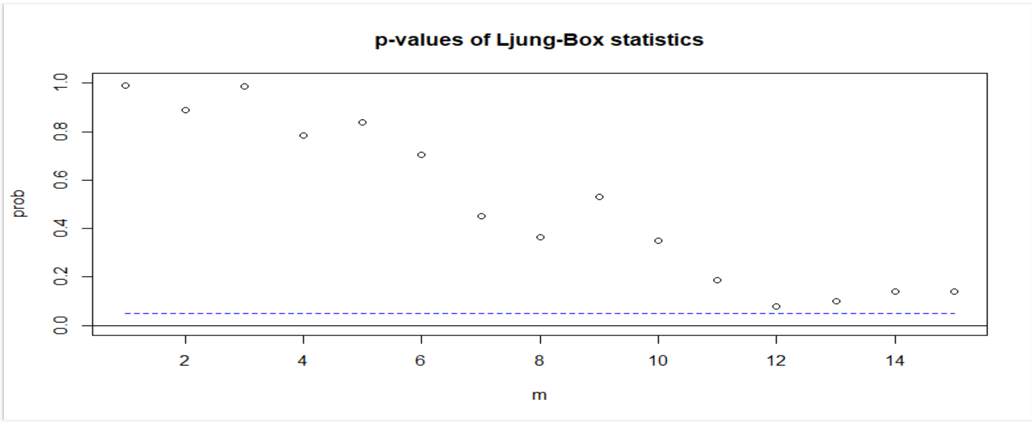

Figure C.13: Sudan Ljung–Box Dependogram

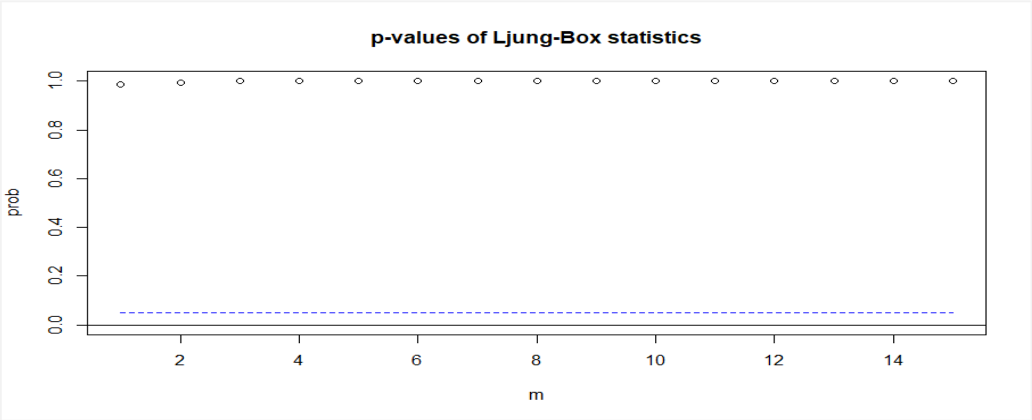

Figure C.14: Tanzania Ljung–Box Dependogram

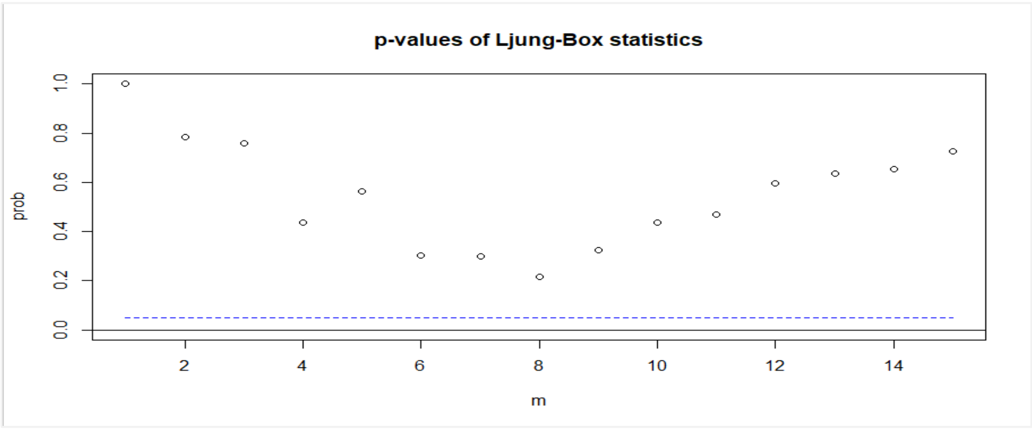

Figure C.15: Tunisia Ljung–Box Dependogram

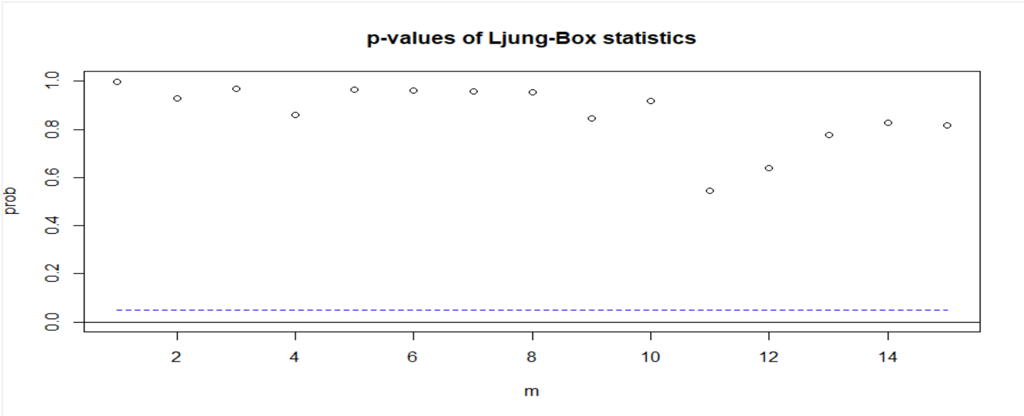

Figure C.16: Uganda Ljung–Box Dependogram

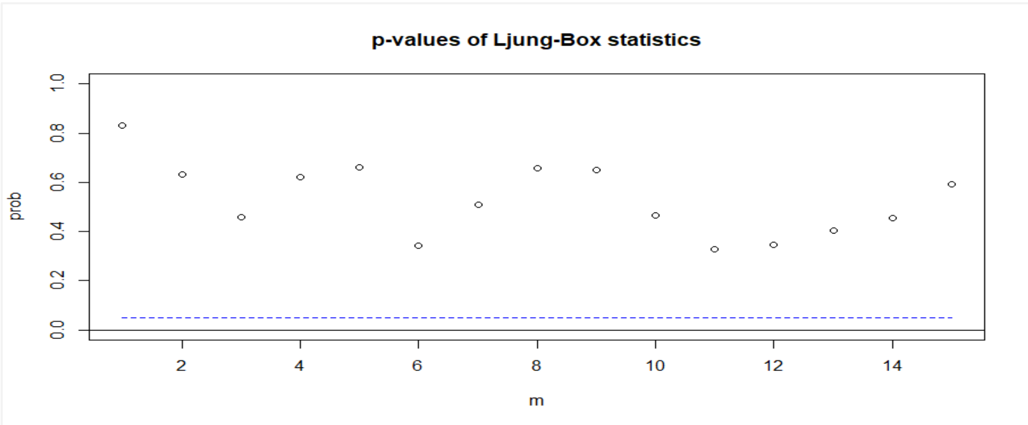

Figure C.17: Zambia Ljung–Box Dependogram

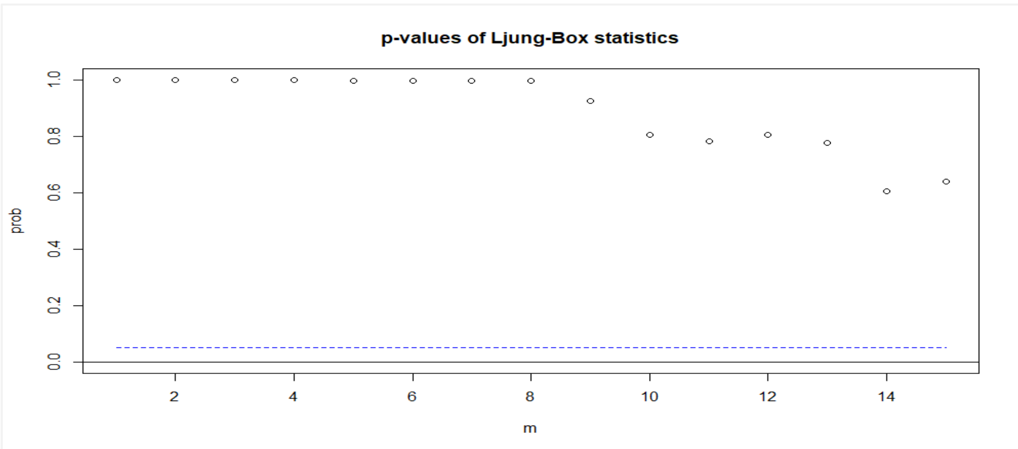

Figure C.18: Ljung–Box Dependogram for Currency MGARCH model

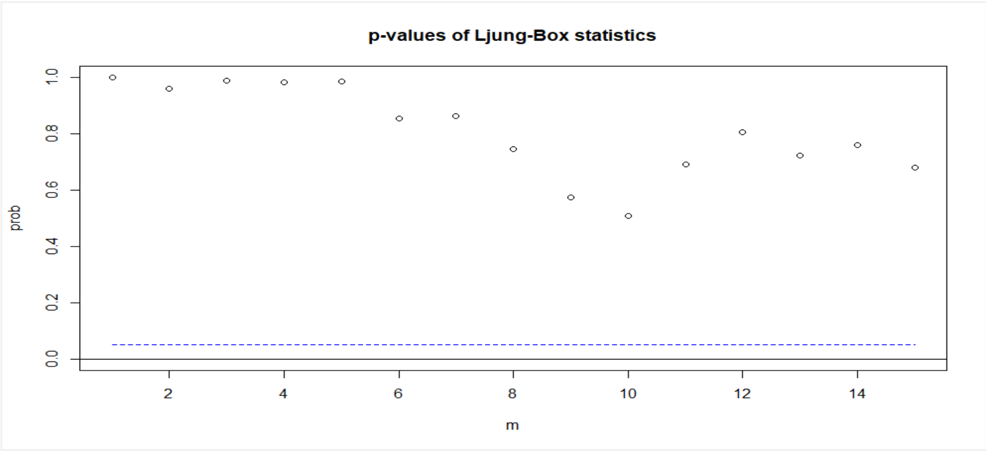

Figure C.19: Ljung–Box Dependogram for Currency MGARCH model

Appendix D. Variance Impulse Response

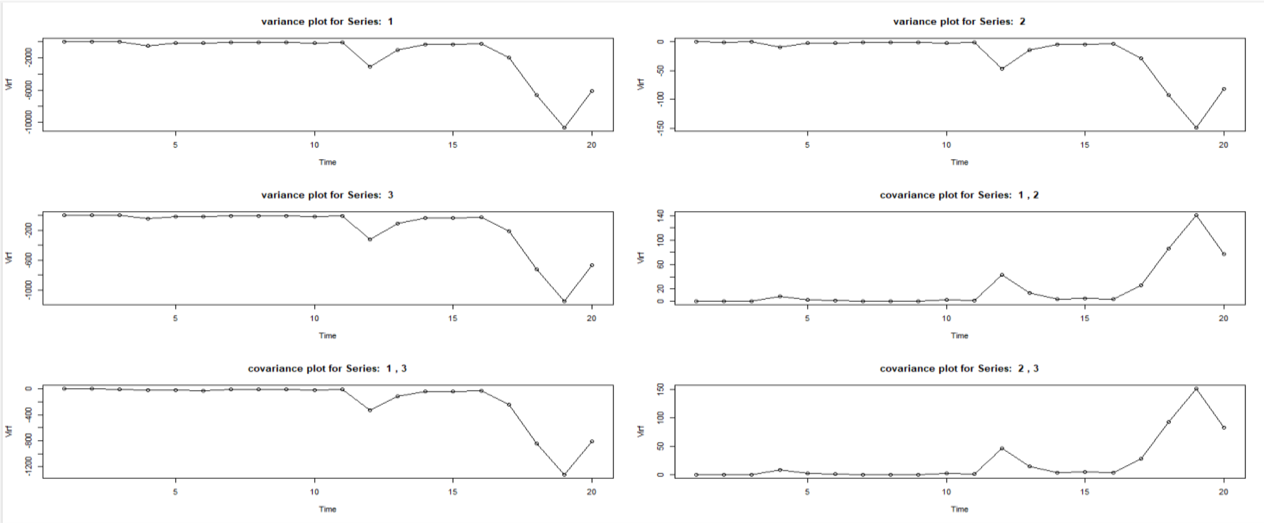

Figure D.1: Angola VIRF (Series order: AOA, Gold and Oil)

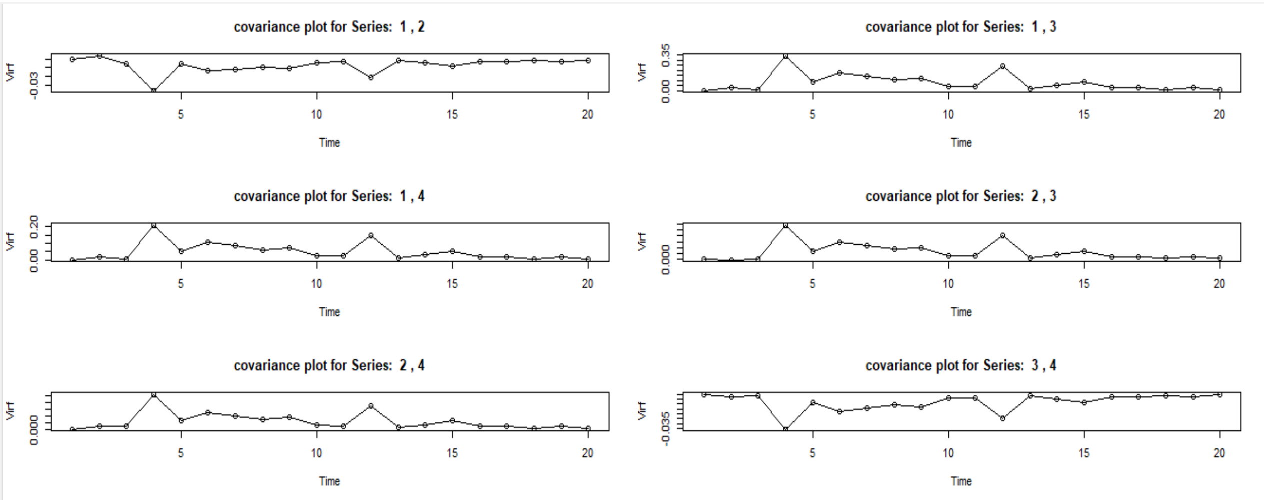

Figure D.2: Botswana VIRF (Series order: BSEDCI, BWP, Gold and Oil)

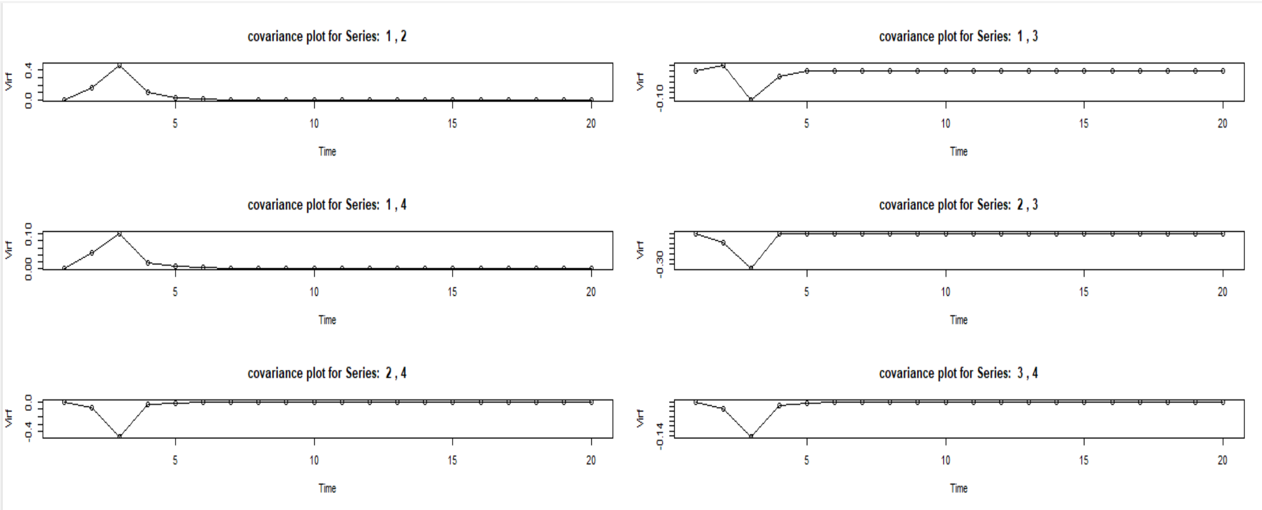

Figure D.3: Côte d'Ivoire VIRF (Series order: BRVM-CI, XOF, Gold and Oil)

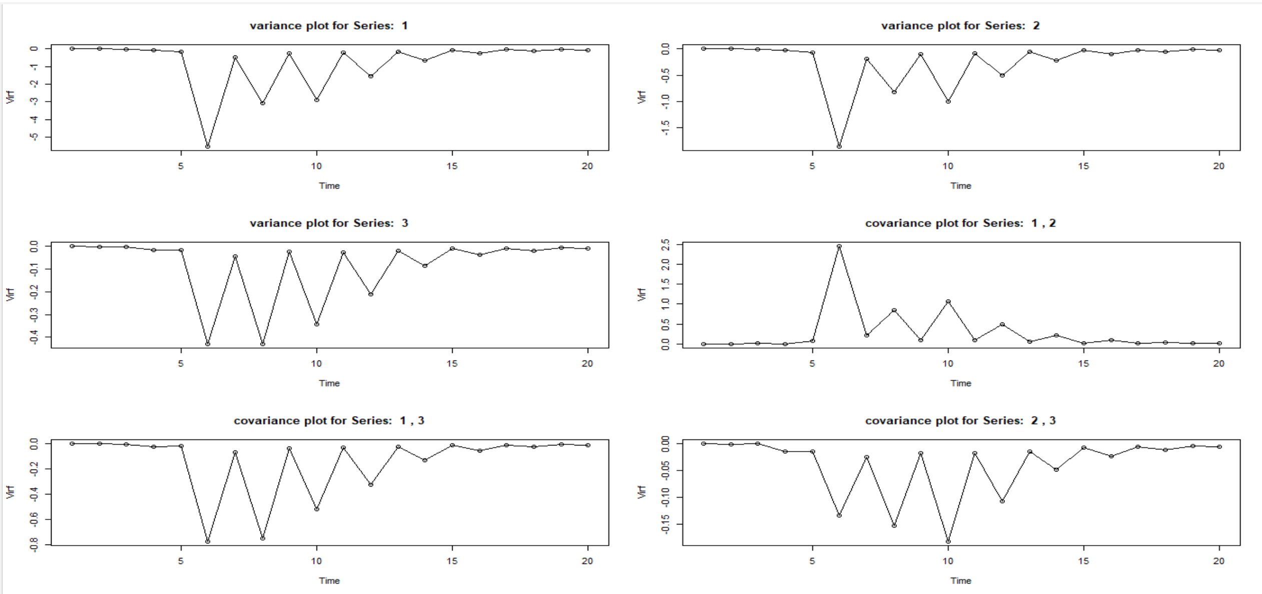

Figure D.4: Dem. Rep. of Congo VIRF (Series order: CDF, Gold and Oil)

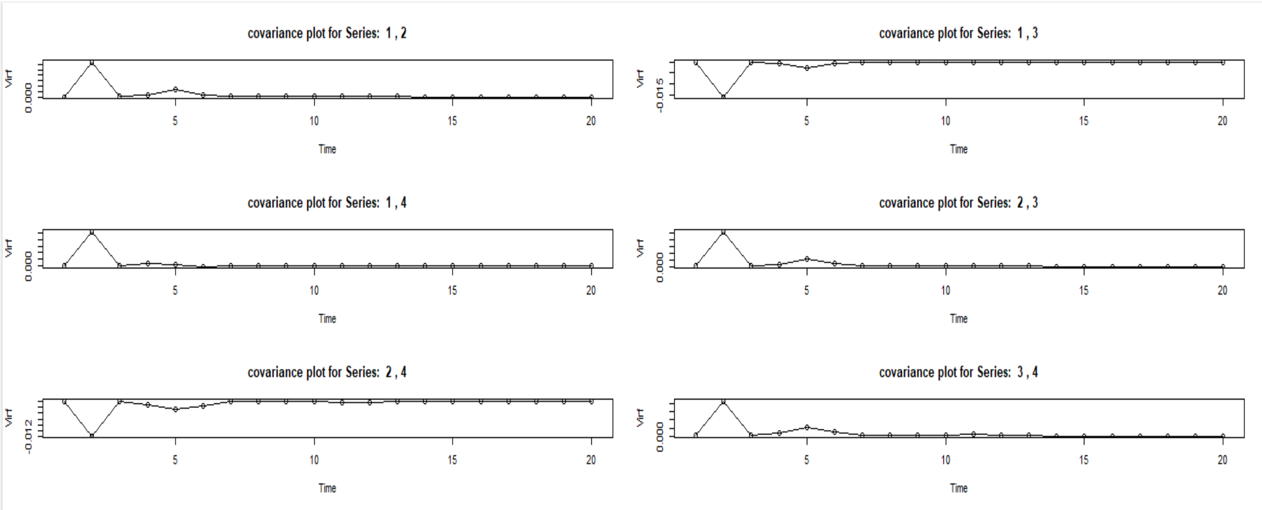

Figure D.5: Arab Rep. of Egypt VIRF (Series order: EGX30, EGP, Gold and Oil)

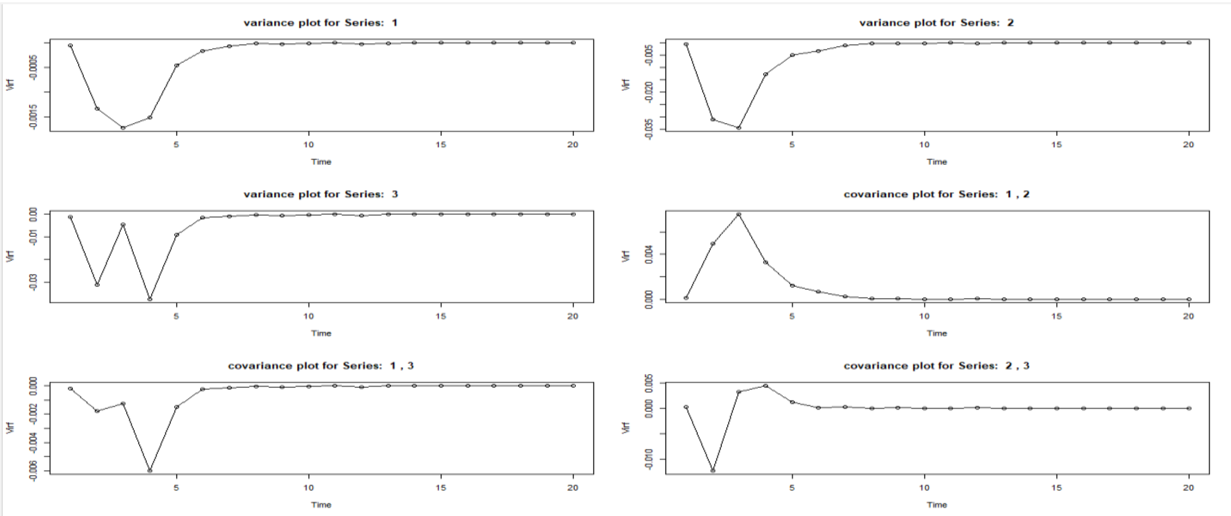

Figure D.6: Ethiopia VIRF (Series order: ETB, Gold and Oil)

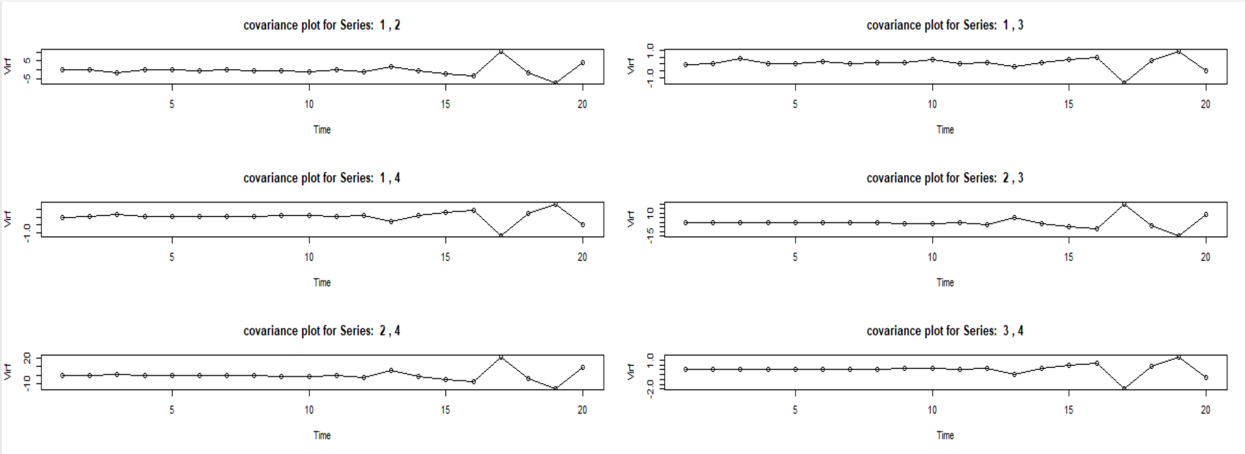

Figure D.7: Ghana VIRF {at t =10} (Series order: GSE, GHS, Gold and Oil)

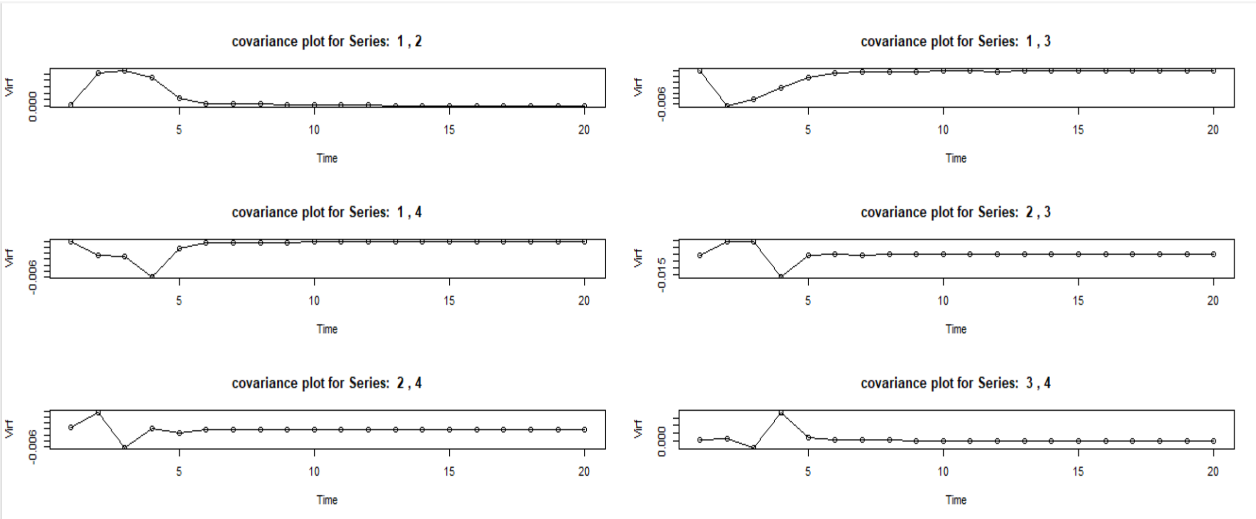

Figure D.8: Kenya VIRF (Series order: NSE, KES, Gold and Oil)

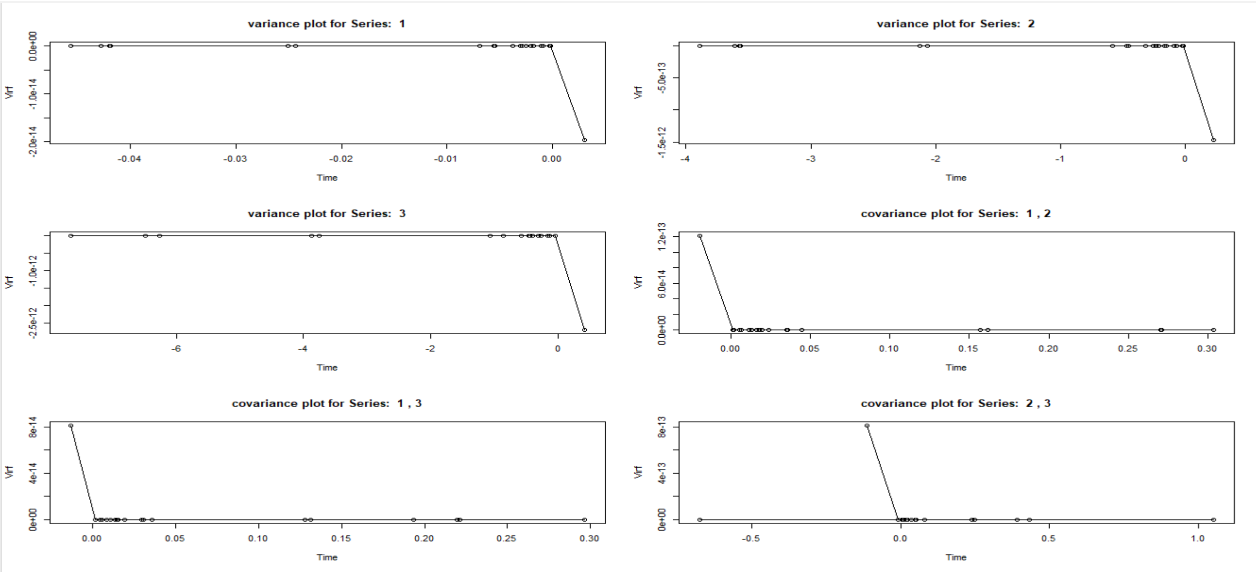

Figure D.9: Libya VIRF {at t =10} (Series order: LYD, Gold and Oil)

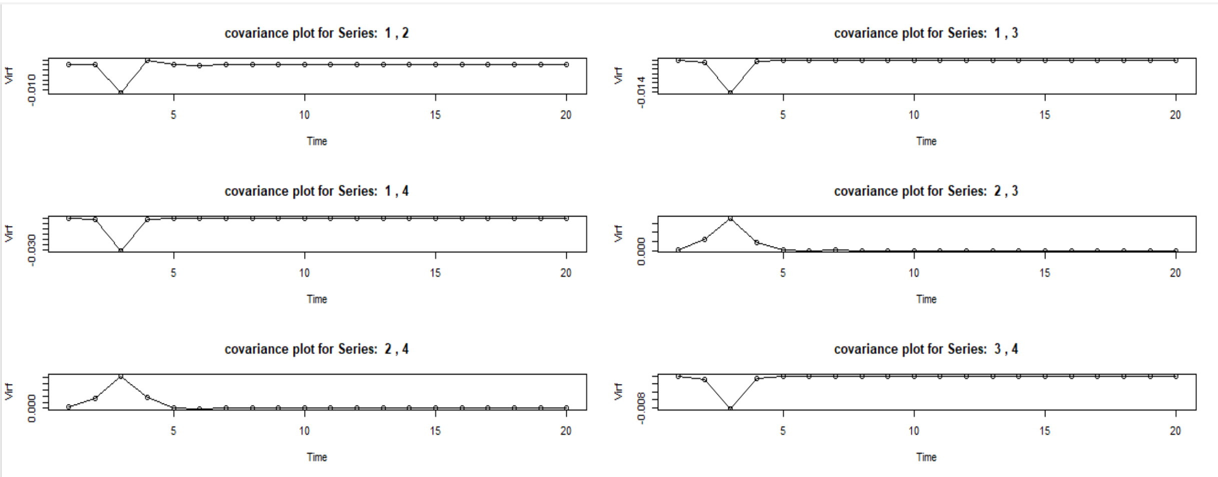

Figure D.10: Morocco VIRF (Series order: MASI, MAD, Gold and Oil)

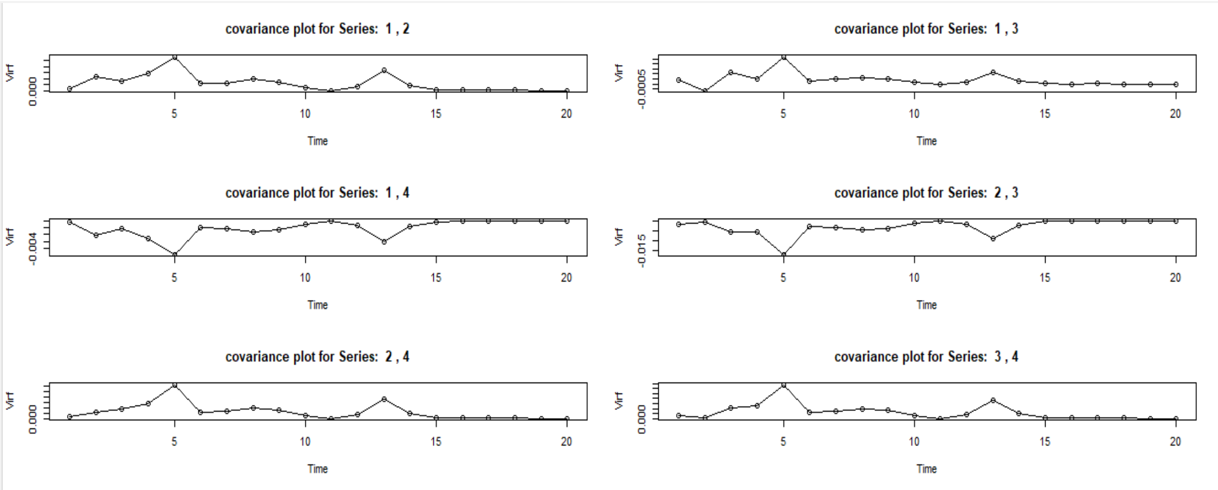

Figure D.11: Nigeria VIRF (Series order: NSE, NGN, Gold and Oil)

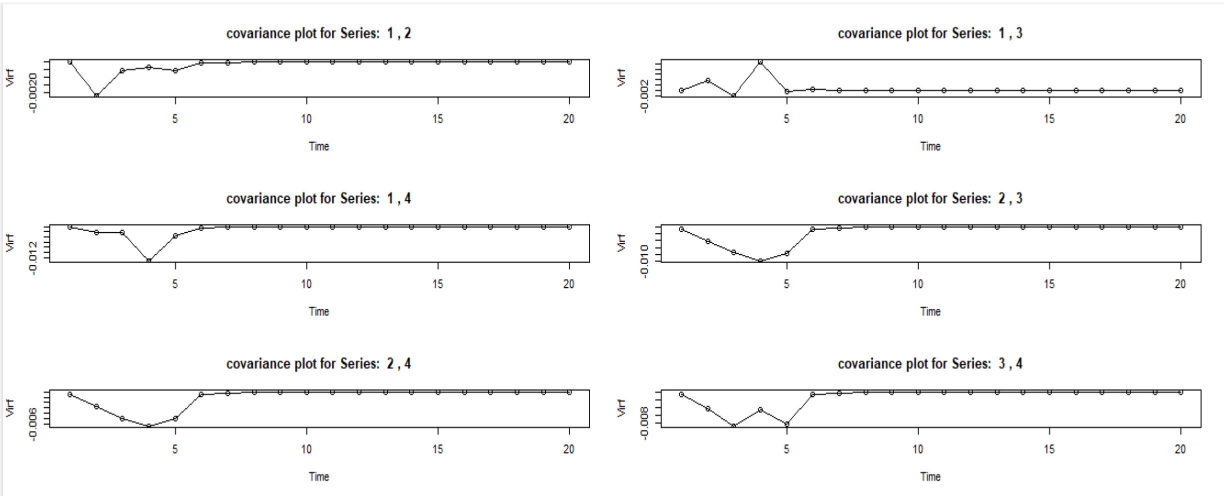

Figure D.12: South Africa VIRF (Series order: SALSI, ZAR, Gold and Oil)

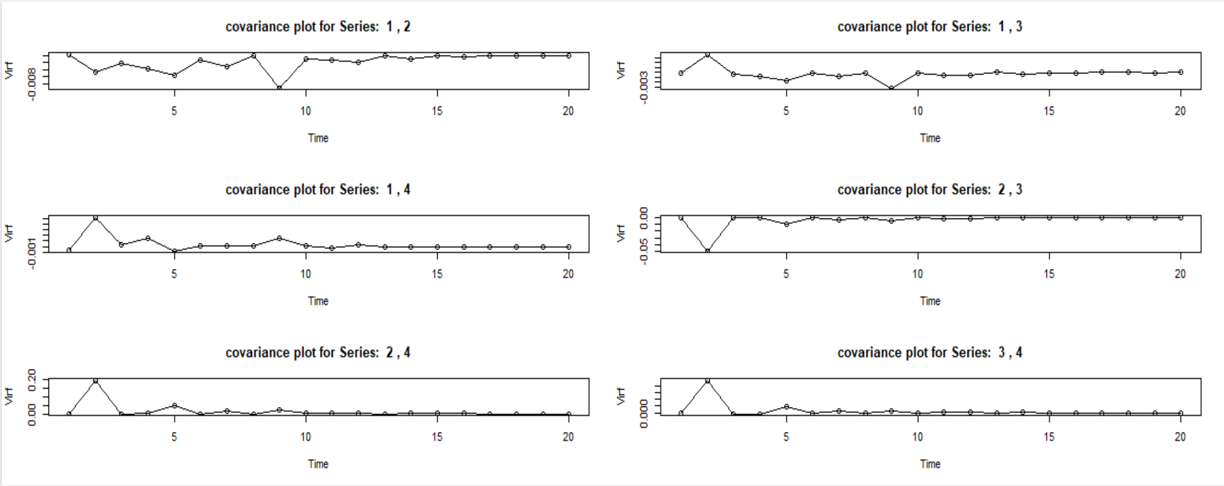

Figure D.13: Sudan VIRF (Series order: Khartoum 30, SDG, Gold and Oil)

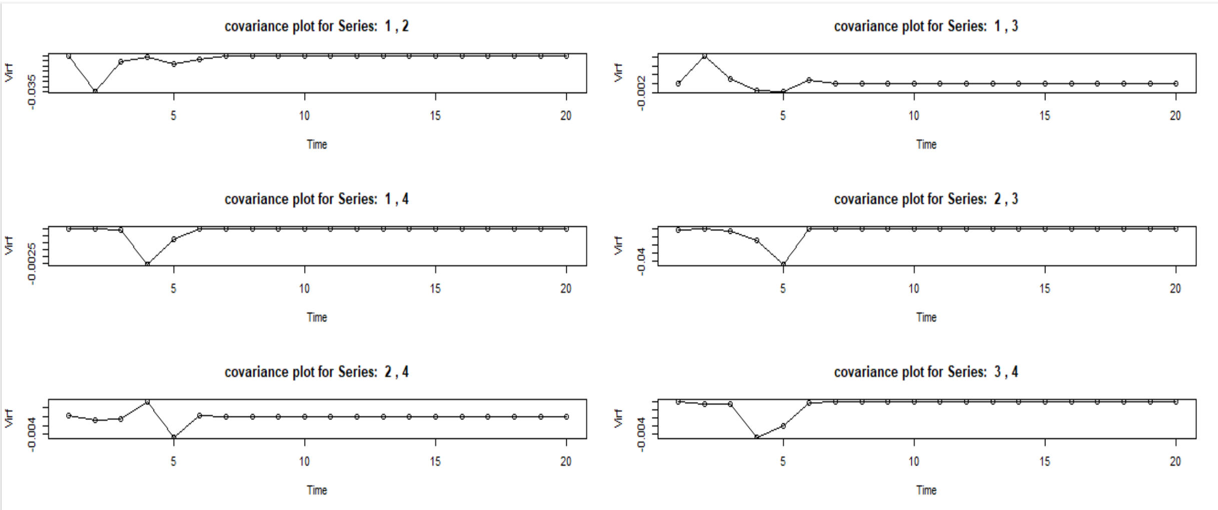

Figure D.14: Tunisia VIRF (Series order: Tunindex, TND, Gold and Oil)

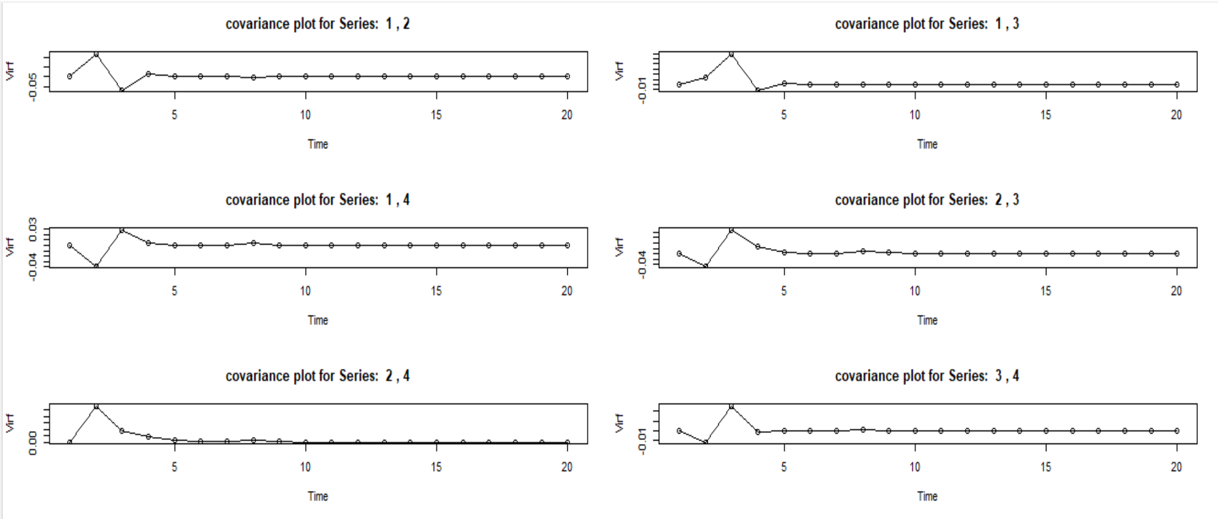

Figure D.15: Uganda VIRF (Series order: UALSI, UGX, Gold and Oil)

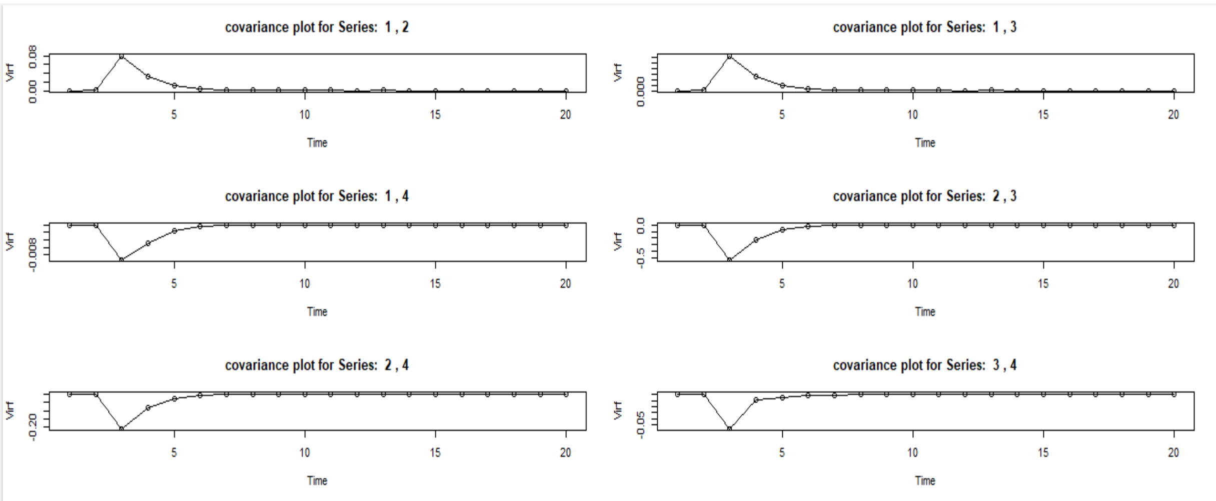

Figure D.16: Zambia VIRF (Series order: UALSI, UGX, Gold and Oil)